

Homework 04

Generalized Linear Models

Jiahao Xu

October 5, 2017

Data analysis

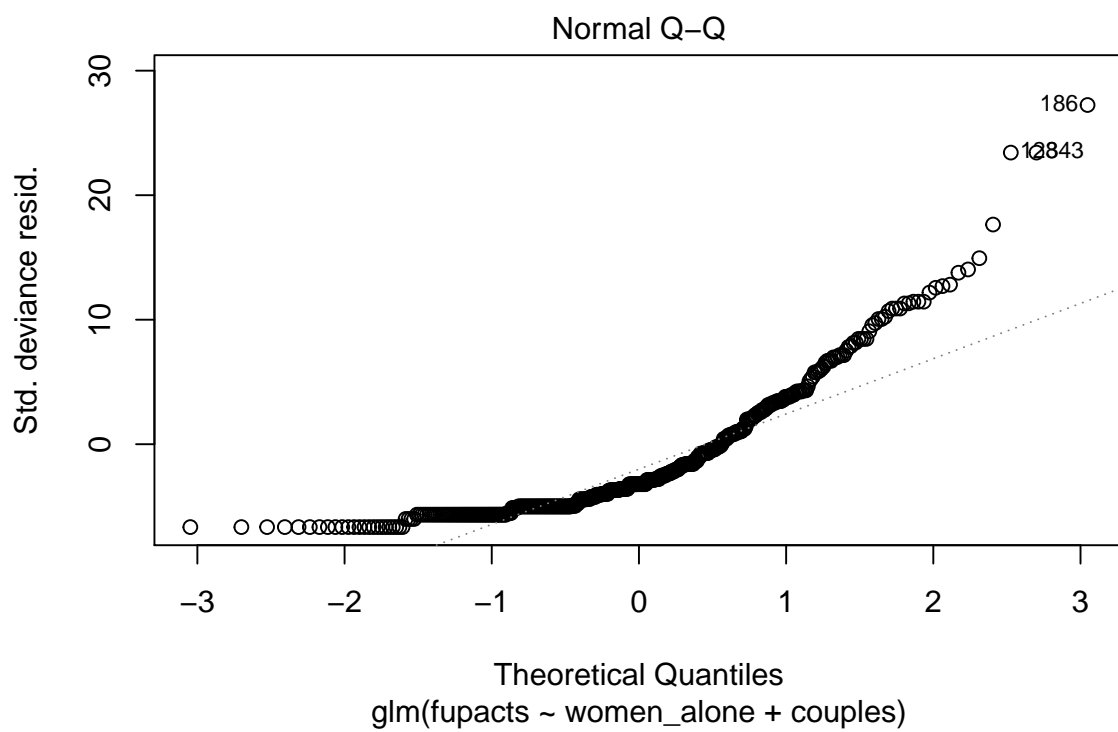
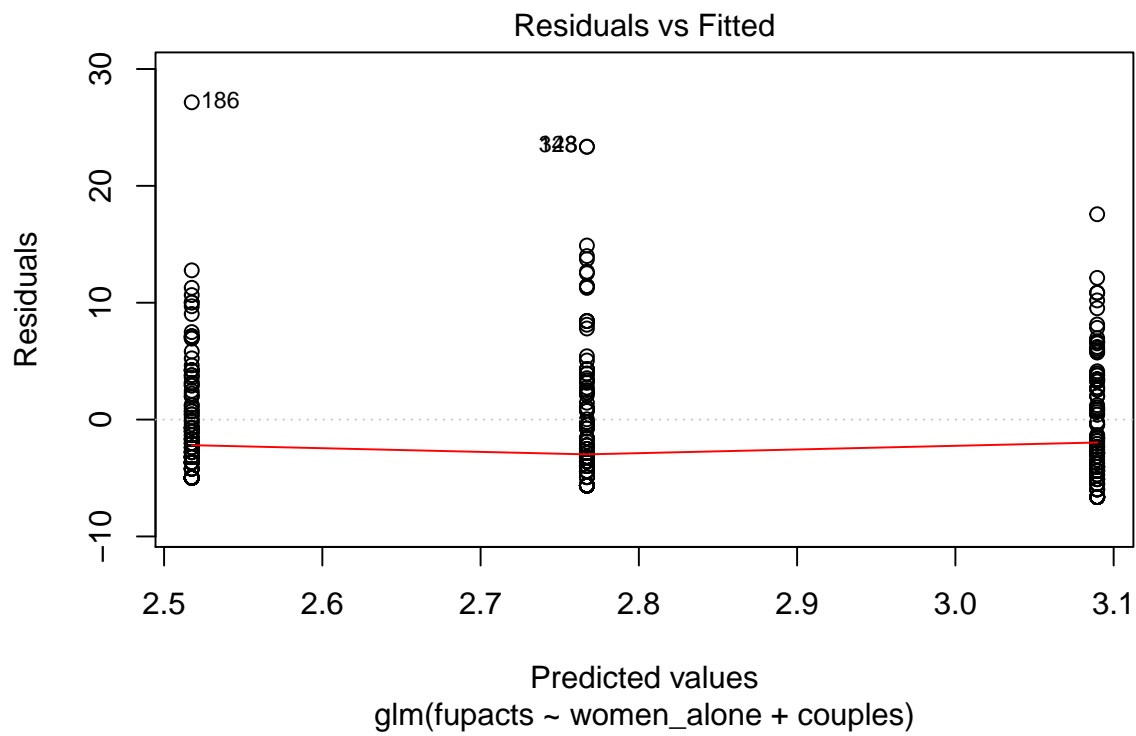
Poisson regression:

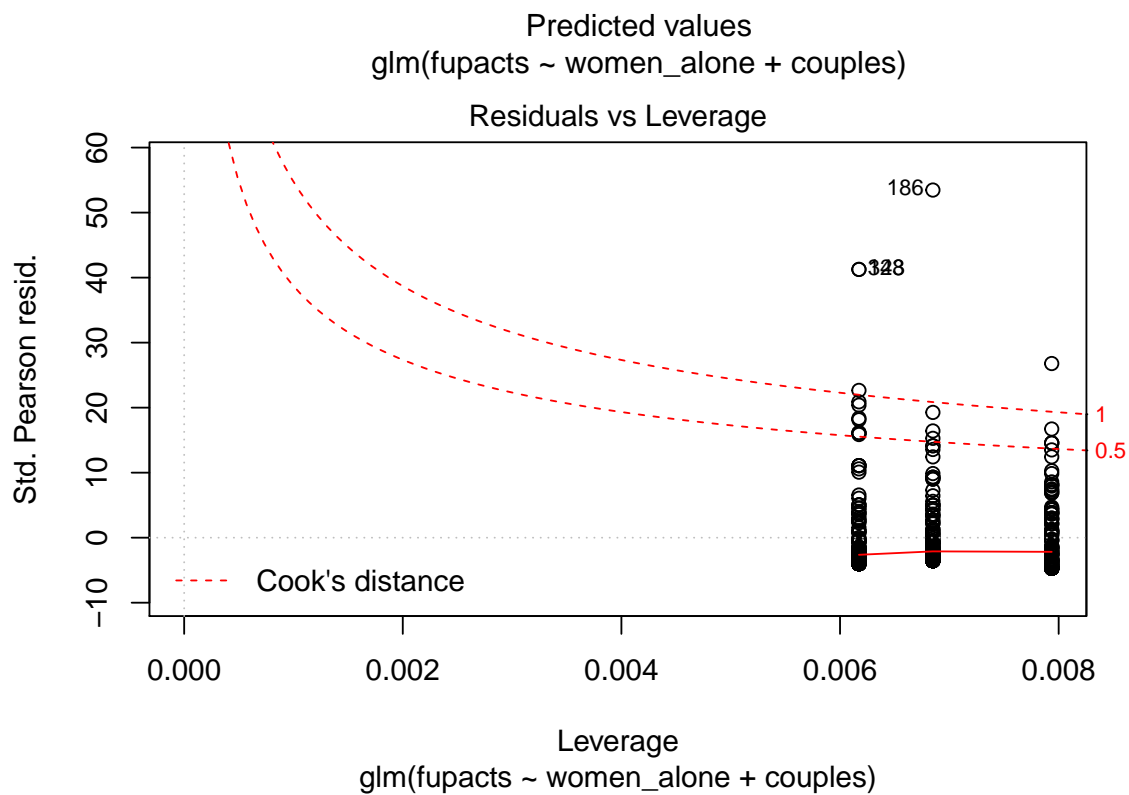
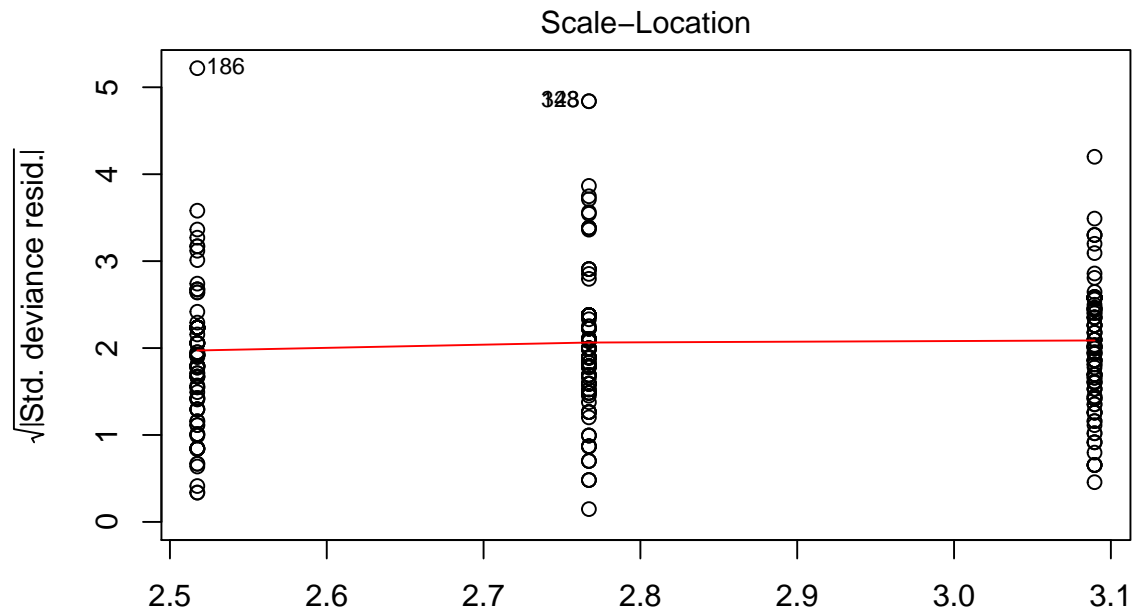
The folder `risky_behavior` contains data from a randomized trial targeting couples at high risk of HIV infection. The intervention provided counseling sessions regarding practices that could reduce their likelihood of contracting HIV. Couples were randomized either to a control group, a group in which just the woman participated, or a group in which both members of the couple participated. One of the outcomes examined after three months was “number of unprotected sex acts”.

1. Model this outcome as a function of treatment assignment using a Poisson regression. Does the model fit well? Is there evidence of overdispersion?

```
risky_behaviors$women_alone<-factor(risky_behaviors$women_alone)
risky_behaviors$couples<-factor(risky_behaviors$couples)
risky_behaviors$fupacts<-round(risky_behaviors$fupacts)
mod1<-glm(fupacts~women_alone+couples, data=risky_behaviors, family=poisson)
summary(mod1)
```

```
##
## Call:
## glm(formula = fupacts ~ women_alone + couples, family = poisson,
##      data = risky_behaviors)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -6.6285  -4.9794  -3.2015   0.9847  27.1502
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)   3.08960    0.01901  162.55  <2e-16 ***
## women_alone1 -0.57212    0.03023  -18.93  <2e-16 ***
## couples1      -0.32243    0.02737  -11.78  <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
##
##      Null deviance: 13299  on 433  degrees of freedom
## Residual deviance: 12925  on 431  degrees of freedom
## AIC: 14256
##
## Number of Fisher Scoring iterations: 6
plot(mod1)
```





```
# The model fits well, because we improve the deviance.
```

```
# check the overdispersion
```

```
tapply(risky_behaviors$fupacts, risky_behaviors$couples,  
       function(x)c(mean=mean(x),variance=var(x)))
```

```
## $`0`
```

```
##      mean  variance
```

```
## 16.83088 634.82000
```

```
##
## $`1`
##      mean  variance
## 15.91358 865.39621

tapply(risky_behaviors$fupacts, risky_behaviors$women_alone,
       function(x) c(mean=mean(x), variance=var(x)))

## $`0`
##      mean  variance
## 18.5625 802.9229
##
## $`1`
##      mean  variance
## 12.39726 533.30316

mod11<-glm(fupacts~women_alone+couples, data=risky_behaviors, family=quasipoisson)
summary.glm(mod11)$dispersion
```

```
## [1] 44.13468
```

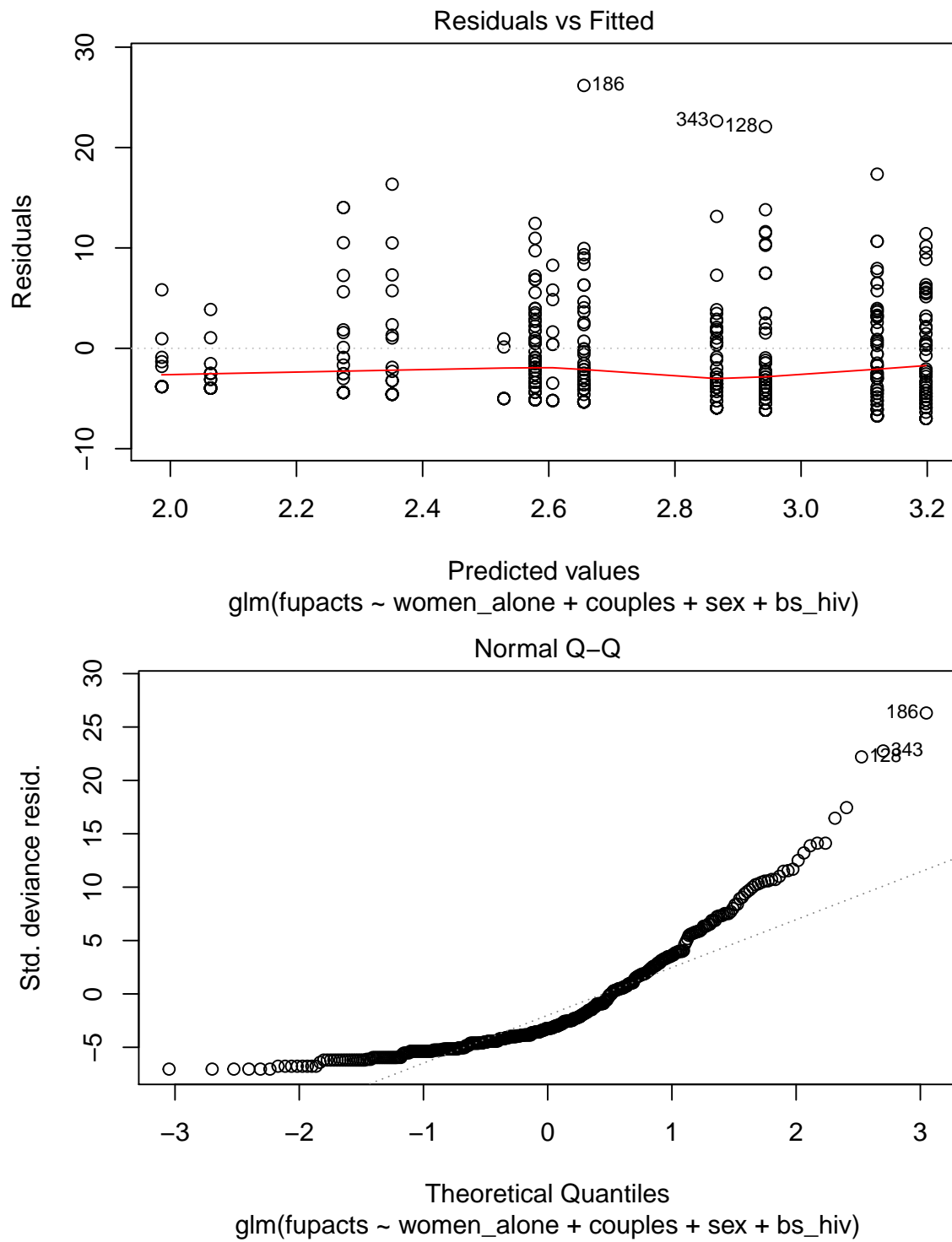
There is evidence of overdispersion: the variance of random component is roughly 40-50 times the size

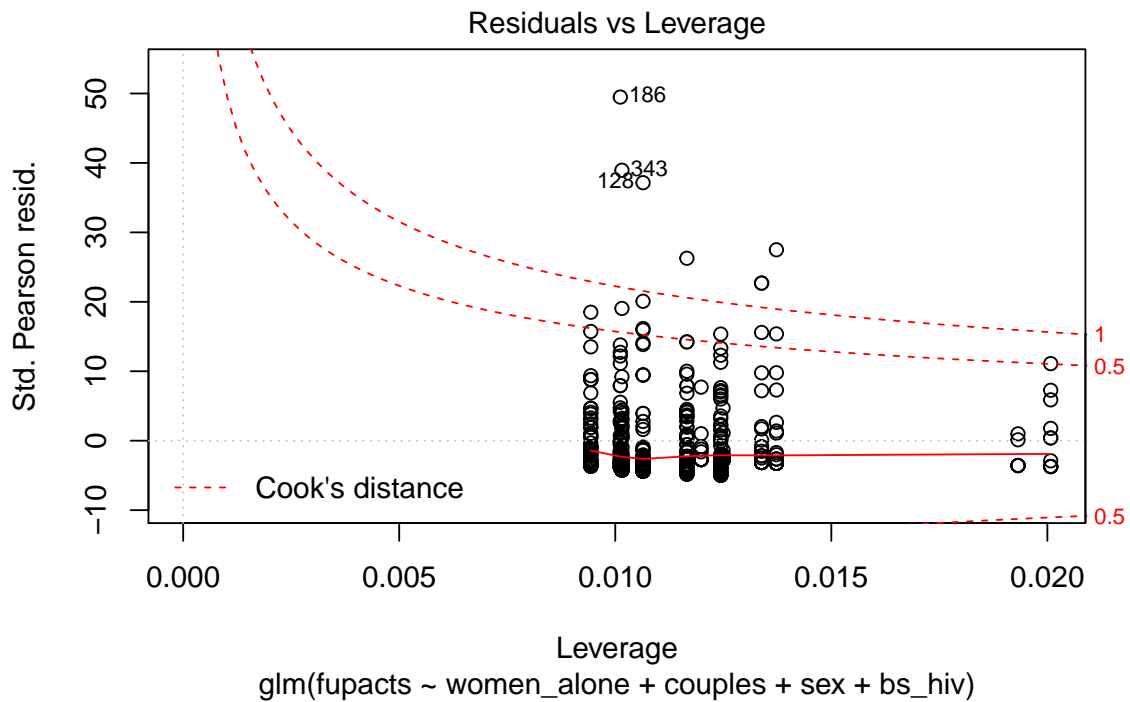
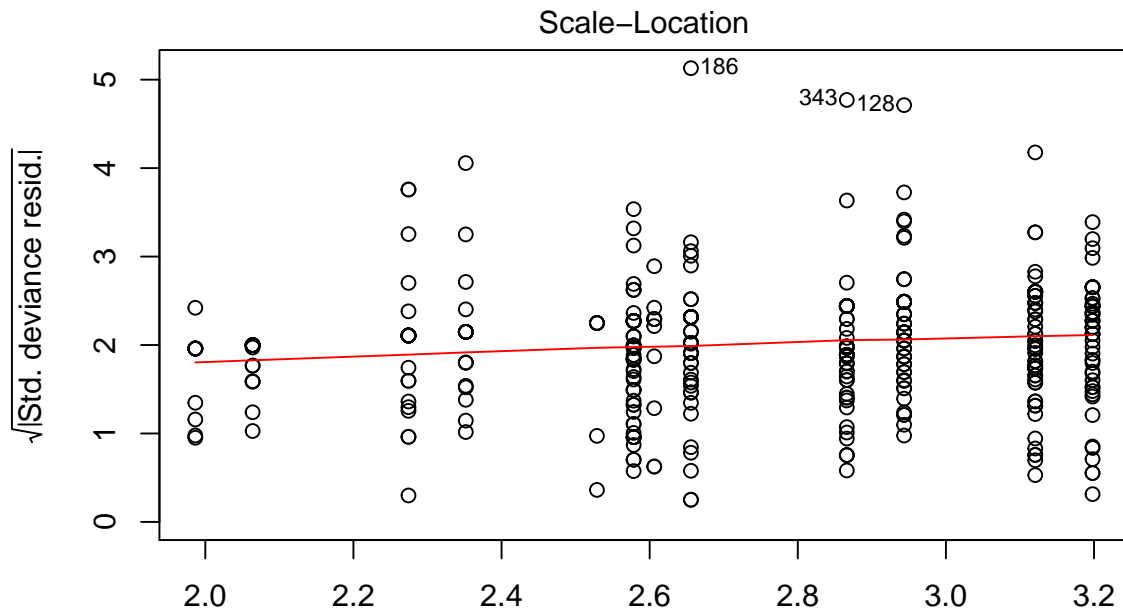
2. Next extend the model to include pre-treatment measures of the outcome and the additional pre-treatment variables included in the dataset. Does the model fit well? Is there evidence of overdispersion?

```
risky_behaviors$women_alone<-factor(risky_behaviors$women_alone)
risky_behaviors$couples<-factor(risky_behaviors$couples)
risky_behaviors$fupacts<-round(risky_behaviors$fupacts)
risky_behaviors$sex<-factor(risky_behaviors$sex)
risky_behaviors$bs_hiv<-factor(risky_behaviors$bs_hiv)
mod2<-glm(fupacts~women_alone+couples+sex+bs_hiv, data=risky_behaviors, family=poisson)
summary(mod2)
```

```
##
## Call:
## glm(formula = fupacts ~ women_alone + couples + sex + bs_hiv,
##      family = poisson, data = risky_behaviors)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -6.998  -4.996  -3.216   1.014  26.182
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)    3.19800    0.02254 141.865 < 2e-16 ***
## women_alone1   -0.54229    0.03026 -17.920 < 2e-16 ***
## couples1       -0.25447    0.02757  -9.231 < 2e-16 ***
## sexman         -0.07737    0.02367  -3.269 0.00108 **
## bs_hivpositive -0.59183    0.03493 -16.941 < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
##
##      Null deviance: 13299  on 433  degrees of freedom
## Residual deviance: 12590  on 429  degrees of freedom
```

```
## AIC: 13924
##
## Number of Fisher Scoring iterations: 6
plot(mod2)
```





The model fits well, because we improve the deviance. And mod2 is better than mod1. It has very little
check the overdispersion

```
tapply(risky_behaviors$fupacts, risky_behaviors$sex,
       function(x) c(mean=mean(x), variance=var(x)))
```

```
## $woman
##      mean  variance
## 16.99078 832.59251
##
```

```
## $man
##      mean  variance
## 15.98618 608.80073

tapply(risky_behaviors$fupacts, risky_behaviors$bs_hiv,
        function(x) c(mean=mean(x), variance=var(x)))

## $negative
##      mean  variance
## 18.38279 804.58220
##
## $positive
##      mean  variance
##  9.907216 371.876718

mod22<-glm(fupacts~women_alone+couples+sex+bs_hiv, data=risky_behaviors, family=quasipoisson)
summary.glm(mod22)$dispersion

## [1] 42.35095
# There is evidence of overdispersion: the variance of random component is roughly 30-40 times the size
```

3. Fit an overdispersed Poisson model. What do you conclude regarding effectiveness of the intervention?

```
mod3<-glm(fupacts~women_alone+couples, data=risky_behaviors, family=quasipoisson)
mod33<-glm(fupacts~women_alone+couples+sex+bs_hiv, data=risky_behaviors, family=quasipoisson)
Anova(mod3)
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: fupacts
##           LR Chisq Df Pr(>Chisq)
## women_alone  8.3362  1  0.003886 **
## couples      3.1425  1  0.076275 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Anova(mod33)
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: fupacts
##           LR Chisq Df Pr(>Chisq)
## women_alone  7.7821  1  0.005277 **
## couples      2.0133  1  0.155925
## sex          0.2524  1  0.615362
## bs_hiv       7.7676  1  0.005319 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

anova(mod3,mod33)
```

```
## Analysis of Deviance Table
##
## Model 1: fupacts ~ women_alone + couples
## Model 2: fupacts ~ women_alone + couples + sex + bs_hiv
##   Resid. Df Resid. Dev Df Deviance
## 1      431      12926
## 2      429      12590  2    335.61
```

```
# It seems the effectiveness of the intervention is less significant.
```

4. These data include responses from both men and women from the participating couples. Does this give you any concern with regard to our modeling assumptions?

```
#This will give me concerns. Because, in the couple data, both men and women will be counted twice for f
```

Comparing logit and probit:

Take one of the data examples from Chapter 5. Fit these data using both logit and probit model. Check that the results are essentially the same (after scaling by factor of 1.6)

```
library(dplyr)

##
## Attaching package: 'dplyr'
## The following object is masked from 'package:car':
##
##   recode
## The following objects are masked from 'package:data.table':
##
##   between, first, last
## The following object is masked from 'package:MASS':
##
##   select
## The following objects are masked from 'package:stats':
##
##   filter, lag
## The following objects are masked from 'package:base':
##
##   intersect, setdiff, setequal, union

library(ggplot2)
nes5200<-read.dta("http://www.stat.columbia.edu/~gelman/arm/examples/nes/nes5200_processed_voters_realiz
nes5200_dt <- data.table(nes5200)
yr <- 1992
nes5200_dt_s<-nes5200_dt[ year==yr & presvote %in% c("1. democrat","2. republican")& !is.na(income)]
nes5200_dt_s<-nes5200_dt_s[,vote_rep:=1*(presvote=="2. republican")]
nes5200_dt_s$vote_rep <- as.integer(nes5200_dt_s$vote_rep)
nes5200_dt_s$gender <- as.integer(nes5200_dt_s$gender)
nes5200_dt_s$race <- as.integer(nes5200_dt_s$race)
nes5200_dt_s$educ1 <- as.integer(nes5200_dt_s$educ1)
nes5200_dt_s$income <- as.integer(nes5200_dt_s$income)
nes5200_dt_s$partyid7 <- as.integer(nes5200_dt_s$partyid7)
nes5200_dt_s$ideo_feel <- as.integer(nes5200_dt_s$ideo_feel)
data1<- nes5200_dt_s %>% select(vote_rep,gender,race,educ1,income,partyid7,ideo_feel)
data1<-na.omit(data1)
model <- glm(vote_rep~gender+race+educ1+partyid7+income+ideo_feel,family = binomial(link="logit"),data=
modell <- glm(vote_rep~gender+race+educ1+partyid7+income+ideo_feel,family = binomial(link="probit"),dat
coef(model)-1.6*coef(modell)
```



```
## (Intercept)      gender      race      educ1      partyid7
## -1.289053557  0.036051158  0.030579112  0.029150924  0.085567398
##      income      ideo_feel
## -0.003307115  0.011713184
```

From the difference of coef, we can see that they are essentially the same

Comparing logit and probit:

construct a dataset where the logit and probit models give different estimates.

Tobit model for mixed discrete/continuous data:

experimental data from the National Supported Work example are available in the folder `lalonge`. Use the treatment indicator and pre-treatment variables to predict post-treatment (1978) earnings using a tobit model. Interpret the model coefficients.

- sample: 1 = NSW; 2 = CPS; 3 = PSID.
- treat: 1 = experimental treatment group (NSW); 0 = comparison group (either from CPS or PSID) - Treatment took place in 1976/1977.
- age = age in years
- educ = years of schooling
- black: 1 if black; 0 otherwise.
- hisp: 1 if Hispanic; 0 otherwise.
- married: 1 if married; 0 otherwise.
- nodegree: 1 if no high school diploma; 0 otherwise.
- re74, re75, re78: real earnings in 1974, 1975 and 1978
- educ_cat = 4 category education variable (1=<hs, 2=hs, 3=sm college, 4=college)

```
##
## Call:
## vglm(formula = re78 ~ sample + treat + age + educ + black + hisp +
##      married + nodegree + educ_cat4 + re74 + re75, family = tobit,
##      data = lalonge)
##
##
## Pearson residuals:
##      Min      1Q  Median      3Q      Max
## mu      -7.894 -0.4138  0.1623  0.53087   9.255
## loge(sd) -1.006 -0.6958 -0.5669  0.05713 128.049
##
## Coefficients:
##      Estimate Std. Error  z value Pr(>|z|)
## (Intercept):1  1.501e+02  6.571e+02   0.228  0.8193
## (Intercept):2  9.039e+00  5.578e-03 1620.618 < 2e-16 ***
## sample        2.467e+03  1.920e+02  12.848 < 2e-16 ***
## treat         3.653e+03  7.141e+02   5.116 3.13e-07 ***
## age          -1.557e+02  6.745e+00 -23.084 < 2e-16 ***
## educ          9.520e+01  5.160e+01   1.845  0.0650 .
## black        -1.069e+03  2.210e+02  -4.837 1.32e-06 ***
## hisp          1.131e+01  2.592e+02   0.044  0.9652
## married      -2.539e+02  1.633e+02  -1.554  0.1201
```

```
## nodegree      9.951e+02  2.128e+02   4.676 2.93e-06 ***
## educ_cat4     3.691e+02  1.479e+02   2.496  0.0126 *
## re74          3.337e-01  1.250e-02  26.691 < 2e-16 ***
## re75          5.564e-01  1.250e-02  44.526 < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Number of linear predictors:  2
##
## Names of linear predictors: mu, loge(sd)
##
## Log-likelihood: -171589.8 on 37321 degrees of freedom
##
## Number of iterations: 5
##
## No Hauck-Donner effect found in any of the estimates
```

Robust linear regression using the t model:

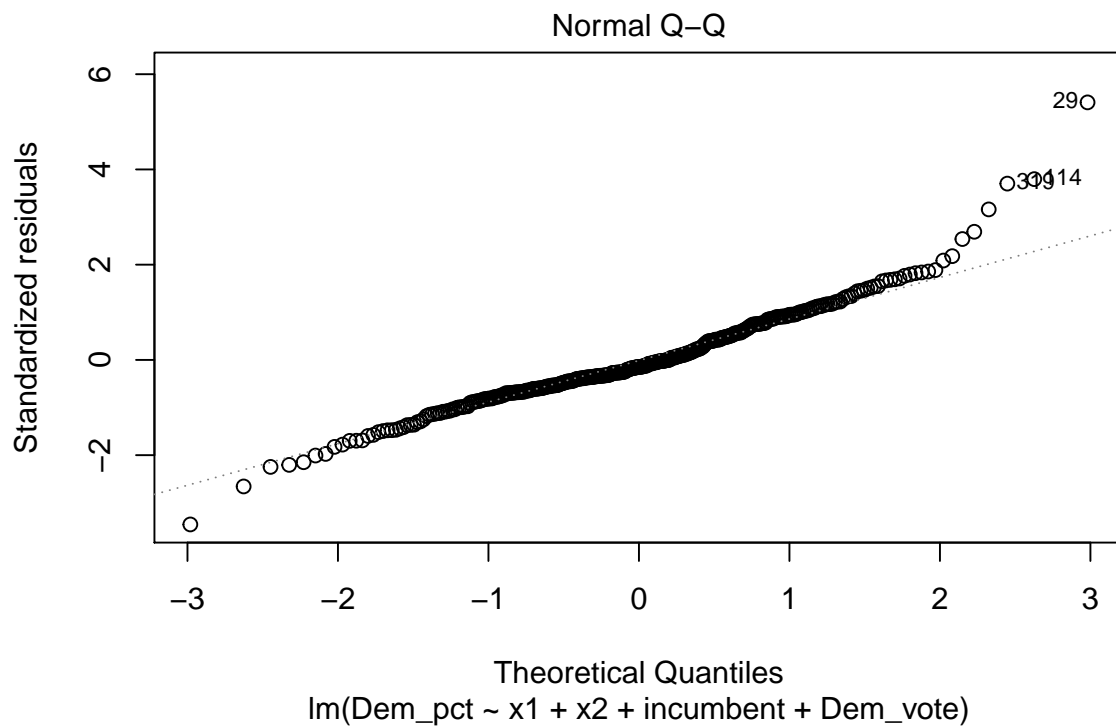
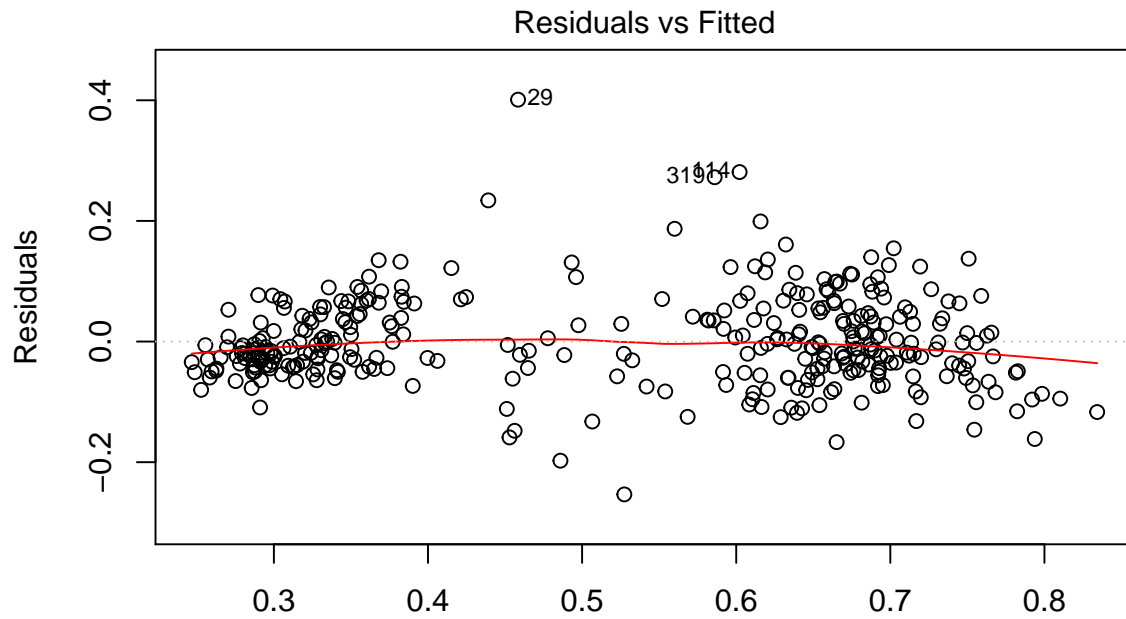
The csv file `congress` has the votes for the Democratic and Republican candidates in each U.S. congressional district in between 1896 and 1992, along with the parties' vote proportions and an indicator for whether the incumbent was running for reelection. For your analysis, just use the elections in 1986 and 1988 that were contested by both parties in both years.

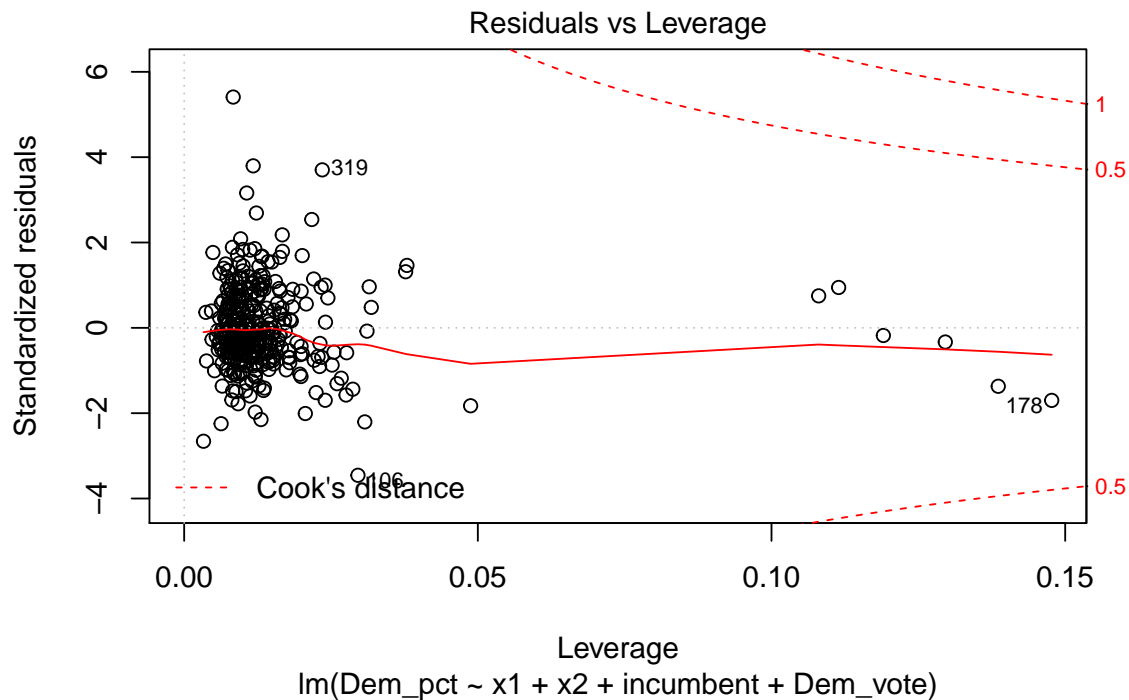
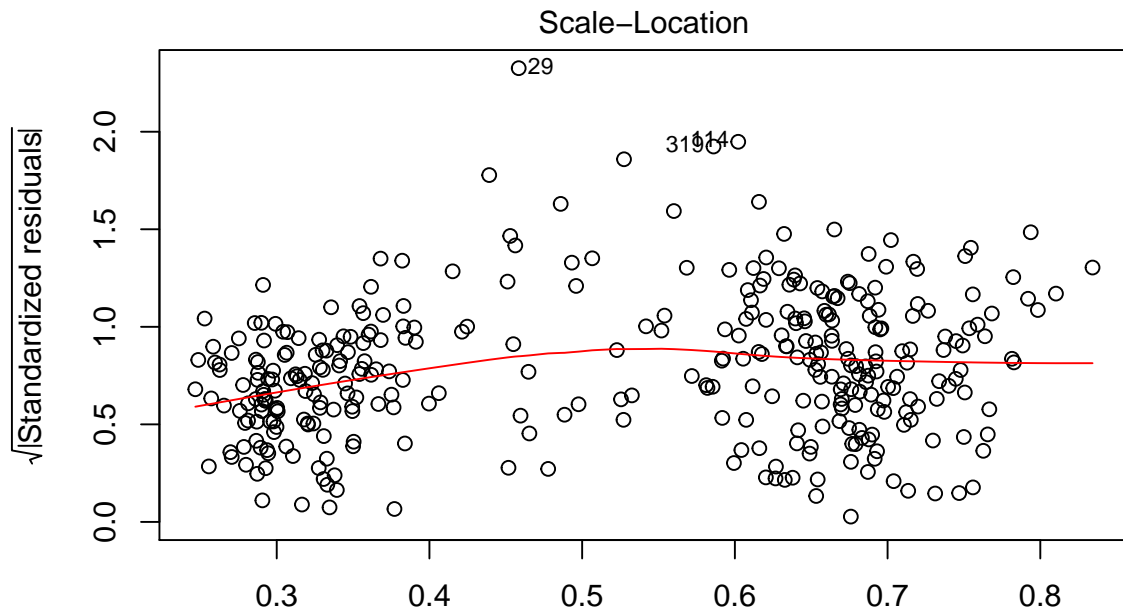
1. Fit a linear regression (with the usual normal-distribution model for the errors) predicting 1988 Democratic vote share from the other variables and assess model fit.

```
data1<-filter(data, year==1988)
data1<-na.omit(data1)
mod111<-lm(Dem_pct~x1+x2+incumbent+Dem_vote,data=data1)
summary(mod111)

##
## Call:
## lm(formula = Dem_pct ~ x1 + x2 + incumbent + Dem_vote, data = data1)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.25339 -0.04459 -0.01095  0.04263  0.40100
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  2.796e-01  1.850e-02  15.112 <2e-16 ***
## x1           3.102e-04  1.862e-04   1.666  0.0966 .
## x2          -4.097e-04  2.720e-04  -1.506  0.1329
## incumbent    1.097e-01  6.530e-03  16.794 <2e-16 ***
## Dem_vote     2.117e-06  1.625e-07  13.029 <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.07445 on 343 degrees of freedom
## Multiple R-squared:  0.85, Adjusted R-squared:  0.8483
## F-statistic:  486 on 4 and 343 DF, p-value: < 2.2e-16
```

```
plot(mod111)
```





The model is fitted, since all the coefficients are significant.

2. Fit a t-regression model predicting 1988 Democratic vote share from the other variables and assess model fit; to fit this model in R you can use the `vglm()` function in the VGLM package or `tlm()` function in the hett package.

```
library(hett)
mod222<-tlm(Dem_pct~x1+x2+incumbent+Dem_vote,data=data1)
summary(mod222)
```

```

## Location model :
##
## Call:
## tlm(lform = Dem_pct ~ x1 + x2 + incumbent + Dem_vote, data = data1)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.231811 -0.037833 -0.002608  0.049479  0.413189
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  2.499e-01  1.597e-02  15.642 < 2e-16 ***
## x1           4.297e-04  1.607e-04   2.673  0.00788 **
## x2          -4.490e-04  2.348e-04  -1.912  0.05673 .
## incumbent    1.030e-01  5.638e-03  18.271 < 2e-16 ***
## Dem_vote     2.311e-06  1.403e-07  16.479 < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Scale parameter(s) as estimated below)
##
##
## Scale Model :
##
## Call:
## tlm(lform = Dem_pct ~ x1 + x2 + incumbent + Dem_vote, data = data1)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2.0000 -1.6659 -0.5783  1.1769  5.6307
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -5.8945     0.1072  -54.98 <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Scale parameter taken to be 2 )
##
##
## Est. degrees of freedom parameter: 3
## Standard error for d.o.f: NA
## No. of iterations of model : 12 in 0.008
## Heteroscedastic t Likelihood : 424.3067

```

3. Which model do you prefer?

I prefer to the second model because ,in the tlm function, we have two models, Location model and Sca

Robust regression for binary data using the robit model:

Use the same data as the previous example with the goal instead of predicting for each district whether it was won by the Democratic or Republican candidate.

1. Fit a standard logistic or probit regression and assess model fit.

```
data1$Dem_pct<-round(data1$Dem_pct)
data1$x1<-factor(data1$x1)
data1$x2<-factor(data1$x2)
data1$incumbent<-factor(data1$incumbent)
data1$Rep_vote<-factor(data1$Rep_vote)
fit1<-glm(Dem_pct~x1+x2+incumbent+Rep_vote,data=data1,family=binomial(link="logit"),control=list(maxit=
summary(fit1)
```

```
##
## Call:
## glm(formula = Dem_pct ~ x1 + x2 + incumbent + Rep_vote, family = binomial(link = "logit"),
##      data = data1, control = list(maxit = 100))
##
## Deviance Residuals:
##      [1]  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
##     [24]  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
##     [47]  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
##     [70]  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
##     [93]  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
##    [116]  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
##    [139]  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
##    [162]  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
##    [185]  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
##    [208]  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
##    [231]  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
##    [254]  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
##    [277]  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
##    [300]  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
##    [323]  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
##    [346]  0  0  0
##
## Coefficients: (96 not defined because of singularities)
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -2.857e+01  1.677e+06      0      1
## x12          -3.207e-13  3.061e+06      0      1
## x13           1.177e-13  1.936e+06      0      1
## x14          -1.002e-13  1.936e+06      0      1
## x15          -6.096e-13  3.061e+06      0      1
## x16          -5.526e-14  3.872e+06      0      1
## x111          3.805e-08  2.738e+06      0      1
## x112          -4.679e-14  1.369e+06      0      1
## x113          -1.484e-13  1.936e+06      0      1
## x114          -1.942e-13  2.371e+06      0      1
## x121          4.763e-14  1.936e+06      0      1
## x122          -1.069e-13  2.371e+06      0      1
## x123          -3.586e-13  2.371e+06      0      1
## x124          -1.894e-14  1.936e+06      0      1
## x125          -2.090e-13  2.371e+06      0      1
## x131          -3.447e-13  2.371e+06      0      1
## x132          -1.363e-13  1.936e+06      0      1
## x133          -1.869e-13  1.936e+06      0      1
## x134          -5.057e-13  3.061e+06      0      1
## x135           1.377e-13  1.936e+06      0      1
```

## x136	8.560e-07	2.738e+06	0	1
## x137	-4.290e-09	2.738e+06	0	1
## x140	-1.123e-13	2.371e+06	0	1
## x141	-5.515e-13	1.936e+06	0	1
## x142	-3.435e-13	1.936e+06	0	1
## x143	-1.187e-13	2.738e+06	0	1
## x144	-1.202e-13	2.371e+06	0	1
## x145	9.797e-15	2.738e+06	0	1
## x146	-1.427e-13	3.353e+06	0	1
## x147	-1.011e-13	2.738e+06	0	1
## x148	-4.765e-14	1.936e+06	0	1
## x149	-2.593e-13	1.936e+06	0	1
## x151	-1.237e-13	1.936e+06	0	1
## x152	-9.915e-14	2.738e+06	0	1
## x153	-1.022e-13	1.369e+06	0	1
## x154	-1.931e-13	2.371e+06	0	1
## x156	-1.763e-05	2.738e+06	0	1
## x161	-2.386e-13	1.369e+06	0	1
## x162	-2.686e-13	1.369e+06	0	1
## x163	-1.649e-13	1.936e+06	0	1
## x164	-3.441e-13	3.061e+06	0	1
## x165	-6.489e-13	3.061e+06	0	1
## x166	-1.205e-13	3.872e+06	0	1
## x167	-2.991e-14	1.936e+06	0	1
## x168	-1.089e-13	1.936e+06	0	1
## x171	2.973e-14	2.371e+06	0	1
## x172	-5.123e-13	3.061e+06	0	1
## x173	-1.886e-13	2.738e+06	0	1
## x181	-2.026e-13	1.936e+06	0	1
## x182	-2.435e-13	1.936e+06	0	1
## x22	3.282e-13	2.738e+06	0	1
## x23	1.163e-13	1.369e+06	0	1
## x24	9.468e-14	1.936e+06	0	1
## x25	8.756e-14	1.369e+06	0	1
## x26	1.974e-13	1.936e+06	0	1
## x27	1.609e-13	1.936e+06	0	1
## x28	1.421e-13	2.371e+06	0	1
## x29	1.036e-13	2.371e+06	0	1
## x210	9.307e-14	2.371e+06	0	1
## x211	2.085e-13	1.936e+06	0	1
## x212	-8.497e-14	1.936e+06	0	1
## x213	-1.306e-14	1.936e+06	0	1
## x214	-1.406e-13	2.371e+06	0	1
## x215	-8.627e-15	2.371e+06	0	1
## x216	-1.663e-13	2.371e+06	0	1
## x217	-1.135e-13	2.738e+06	0	1
## x218	1.748e-13	2.738e+06	0	1
## x219	1.191e-13	2.371e+06	0	1
## x220	-2.286e-13	2.738e+06	0	1
## x221	-1.882e-13	4.742e+06	0	1
## x222	5.427e-14	2.738e+06	0	1
## x223	1.364e-13	2.371e+06	0	1
## x224	8.785e-14	2.371e+06	0	1
## x225	-1.762e-05	2.738e+06	0	1

## x226	1.471e-13	1.936e+06	0	1
## x227	-5.044e-14	4.107e+06	0	1
## x228	-1.763e-05	3.061e+06	0	1
## x229	-2.141e-13	2.371e+06	0	1
## x230	8.269e-07	3.061e+06	0	1
## x231	1.534e-13	4.107e+06	0	1
## x232	-1.762e-05	3.061e+06	0	1
## x233	-3.075e-14	2.738e+06	0	1
## x234	8.389e-07	3.061e+06	0	1
## x235	-2.303e-13	2.738e+06	0	1
## x236	5.059e-08	3.061e+06	0	1
## x237	-2.856e-13	2.738e+06	0	1
## x238	-5.713e+01	3.061e+06	0	1
## x239	-2.114e-13	2.738e+06	0	1
## x240	6.110e-14	4.742e+06	0	1
## x241	2.298e-14	2.738e+06	0	1
## x242	-1.901e-13	4.742e+06	0	1
## x243	-2.422e-13	2.738e+06	0	1
## x244	-1.842e-05	3.061e+06	0	1
## x245	-1.367e-13	2.738e+06	0	1
## x298	NA	NA	NA	NA
## incumbent0	1.733e-14	3.061e+06	0	1
## incumbent1	5.713e+01	1.936e+06	0	1
## Rep_vote13848	5.713e+01	3.353e+06	0	1
## Rep_vote14543	8.487e-07	3.353e+06	0	1
## Rep_vote20729	7.197e-08	3.622e+06	0	1
## Rep_vote24313	8.756e-07	3.872e+06	0	1
## Rep_vote24804	1.900e-08	4.936e+06	0	1
## Rep_vote27536	4.293e-08	3.061e+06	0	1
## Rep_vote28645	NA	NA	NA	NA
## Rep_vote28831	8.663e-07	3.622e+06	0	1
## Rep_vote29156	4.548e-08	3.872e+06	0	1
## Rep_vote30944	4.699e-08	3.622e+06	0	1
## Rep_vote33475	8.198e-07	3.353e+06	0	1
## Rep_vote33692	8.600e-07	2.738e+06	0	1
## Rep_vote34659	2.678e-08	3.353e+06	0	1
## Rep_vote34909	-1.764e-05	3.353e+06	0	1
## Rep_vote36017	9.235e-08	4.107e+06	0	1
## Rep_vote36183	-1.761e-05	3.622e+06	0	1
## Rep_vote36309	5.529e-08	3.353e+06	0	1
## Rep_vote36719	5.847e-08	3.872e+06	0	1
## Rep_vote36801	-1.761e-05	3.872e+06	0	1
## Rep_vote36835	9.734e-08	3.353e+06	0	1
## Rep_vote37454	5.713e+01	4.936e+06	0	1
## Rep_vote37693	8.954e-07	3.061e+06	0	1
## Rep_vote37958	8.482e-07	3.061e+06	0	1
## Rep_vote38033	5.747e-09	2.738e+06	0	1
## Rep_vote38381	2.647e-08	3.872e+06	0	1
## Rep_vote39749	-1.844e-05	3.061e+06	0	1
## Rep_vote40277	4.312e-08	3.061e+06	0	1
## Rep_vote40316	8.295e-08	3.353e+06	0	1
## Rep_vote40732	1.772e-05	2.371e+06	0	1
## Rep_vote41076	6.560e-08	3.061e+06	0	1
## Rep_vote41478	1.846e-05	2.371e+06	0	1

## Rep_vote42220	-1.842e-09	3.872e+06	0	1
## Rep_vote42664	-9.867e-09	3.061e+06	0	1
## Rep_vote43833	-1.844e-05	3.061e+06	0	1
## Rep_vote44043	NA	NA	NA	NA
## Rep_vote45239	8.115e-08	3.061e+06	0	1
## Rep_vote45954	-1.843e-05	3.872e+06	0	1
## Rep_vote46130	8.690e-07	4.107e+06	0	1
## Rep_vote46552	-1.763e-05	3.061e+06	0	1
## Rep_vote46622	-1.762e-05	2.738e+06	0	1
## Rep_vote47039	-1.761e-05	4.107e+06	0	1
## Rep_vote47071	-5.013e-09	2.738e+06	0	1
## Rep_vote47293	2.961e-08	3.061e+06	0	1
## Rep_vote47625	8.536e-07	2.738e+06	0	1
## Rep_vote47929	3.710e-08	3.622e+06	0	1
## Rep_vote47957	8.325e-07	3.061e+06	0	1
## Rep_vote48375	1.436e-08	3.061e+06	0	1
## Rep_vote49498	8.883e-08	3.353e+06	0	1
## Rep_vote49620	8.650e-07	3.061e+06	0	1
## Rep_vote49657	8.272e-07	3.353e+06	0	1
## Rep_vote49733	-1.763e-05	3.061e+06	0	1
## Rep_vote49753	NA	NA	NA	NA
## Rep_vote49855	8.719e-07	3.061e+06	0	1
## Rep_vote50050	5.104e-08	2.738e+06	0	1
## Rep_vote50229	1.769e-05	3.061e+06	0	1
## Rep_vote50356	8.695e-07	3.353e+06	0	1
## Rep_vote50710	NA	NA	NA	NA
## Rep_vote50954	NA	NA	NA	NA
## Rep_vote51628	8.327e-07	3.353e+06	0	1
## Rep_vote51985	-1.772e-05	2.738e+06	0	1
## Rep_vote52402	-1.841e-05	3.353e+06	0	1
## Rep_vote52807	1.065e-08	3.061e+06	0	1
## Rep_vote53109	8.624e-07	3.622e+06	0	1
## Rep_vote53518	8.577e-07	3.353e+06	0	1
## Rep_vote53588	-1.841e-05	3.622e+06	0	1
## Rep_vote53902	5.713e+01	3.061e+06	0	1
## Rep_vote54034	8.211e-07	3.622e+06	0	1
## Rep_vote54195	8.399e-07	3.061e+06	0	1
## Rep_vote54528	-8.246e-09	2.738e+06	0	1
## Rep_vote55197	-1.762e-05	2.371e+06	0	1
## Rep_vote55511	NA	NA	NA	NA
## Rep_vote56630	8.230e-08	3.061e+06	0	1
## Rep_vote56656	-1.761e-05	3.622e+06	0	1
## Rep_vote56893	5.713e+01	4.541e+06	0	1
## Rep_vote56963	8.526e-07	2.371e+06	0	1
## Rep_vote57387	4.078e-09	3.061e+06	0	1
## Rep_vote57587	8.201e-07	2.738e+06	0	1
## Rep_vote57658	-1.761e-05	3.061e+06	0	1
## Rep_vote59128	8.185e-07	2.371e+06	0	1
## Rep_vote59287	-8.398e-09	2.738e+06	0	1
## Rep_vote59688	8.446e-07	3.622e+06	0	1
## Rep_vote59827	-1.848e-05	3.353e+06	0	1
## Rep_vote59877	8.477e-07	2.738e+06	0	1
## Rep_vote59907	8.604e-07	3.872e+06	0	1
## Rep_vote60037	9.661e-08	2.738e+06	0	1

## Rep_vote60346	5.532e-08	2.738e+06	0	1
## Rep_vote60453	7.304e-08	3.622e+06	0	1
## Rep_vote60559	8.745e-07	2.738e+06	0	1
## Rep_vote60646	5.760e-08	2.738e+06	0	1
## Rep_vote60946	-1.843e-05	2.738e+06	0	1
## Rep_vote62056	-1.839e-05	3.353e+06	0	1
## Rep_vote62564	6.516e-08	3.622e+06	0	1
## Rep_vote63013	8.436e-07	3.353e+06	0	1
## Rep_vote63372	4.428e-08	3.061e+06	0	1
## Rep_vote63959	-1.762e-05	2.371e+06	0	1
## Rep_vote64174	5.983e-08	3.353e+06	0	1
## Rep_vote64491	8.453e-07	2.738e+06	0	1
## Rep_vote64750	8.911e-08	1.936e+06	0	1
## Rep_vote65278	-1.762e-05	2.738e+06	0	1
## Rep_vote65307	8.520e-07	4.107e+06	0	1
## Rep_vote65393	2.608e-08	3.872e+06	0	1
## Rep_vote65410	9.634e-08	3.353e+06	0	1
## Rep_vote66521	7.108e-08	4.107e+06	0	1
## Rep_vote66935	9.326e-08	3.061e+06	0	1
## Rep_vote66972	-1.762e-05	3.872e+06	0	1
## Rep_vote67073	9.644e-08	3.061e+06	0	1
## Rep_vote67337	8.470e-07	3.061e+06	0	1
## Rep_vote67461	5.533e-08	3.872e+06	0	1
## Rep_vote67604	7.317e-08	3.353e+06	0	1
## Rep_vote67709	8.631e-07	2.738e+06	0	1
## Rep_vote67759	9.055e-08	3.622e+06	0	1
## Rep_vote68165	8.236e-07	3.353e+06	0	1
## Rep_vote68226	2.000e-08	3.622e+06	0	1
## Rep_vote68363	-1.839e-05	3.353e+06	0	1
## Rep_vote68788	-1.763e-05	3.061e+06	0	1
## Rep_vote68978	8.532e-07	4.107e+06	0	1
## Rep_vote69165	1.129e-08	3.061e+06	0	1
## Rep_vote69303	5.365e-08	2.738e+06	0	1
## Rep_vote70359	-7.060e-09	3.622e+06	0	1
## Rep_vote70534	-1.762e-05	3.353e+06	0	1
## Rep_vote71560	-1.761e-05	2.738e+06	0	1
## Rep_vote71661	4.108e-08	3.061e+06	0	1
## Rep_vote71905	-8.539e-09	2.738e+06	0	1
## Rep_vote72189	8.374e-07	3.061e+06	0	1
## Rep_vote72489	-1.762e-05	2.371e+06	0	1
## Rep_vote73425	8.474e-07	2.738e+06	0	1
## Rep_vote73659	5.737e-08	3.622e+06	0	1
## Rep_vote73981	8.399e-07	3.353e+06	0	1
## Rep_vote74275	8.923e-07	2.738e+06	0	1
## Rep_vote74296	-1.841e-05	3.061e+06	0	1
## Rep_vote74357	7.998e-08	2.738e+06	0	1
## Rep_vote74405	6.881e-08	3.622e+06	0	1
## Rep_vote74682	-1.761e-05	2.738e+06	0	1
## Rep_vote74824	8.269e-07	3.061e+06	0	1
## Rep_vote75462	5.986e-08	2.738e+06	0	1
## Rep_vote75571	-6.637e-09	2.738e+06	0	1
## Rep_vote76008	-5.602e-09	3.061e+06	0	1
## Rep_vote76179	NA	NA	NA	NA
## Rep_vote76531	8.159e-07	3.622e+06	0	1

## Rep_vote77184	8.179e-07	3.622e+06	0	1
## Rep_vote77186	1.923e-08	3.061e+06	0	1
## Rep_vote78028	3.979e-08	2.738e+06	0	1
## Rep_vote78307	8.657e-07	3.061e+06	0	1
## Rep_vote78396	9.934e-08	2.371e+06	0	1
## Rep_vote78478	-1.763e-05	3.353e+06	0	1
## Rep_vote78626	8.223e-07	3.622e+06	0	1
## Rep_vote78909	-1.765e-05	2.738e+06	0	1
## Rep_vote80181	-1.761e-05	2.738e+06	0	1
## Rep_vote80212	-1.844e-05	3.622e+06	0	1
## Rep_vote80372	2.611e-09	2.738e+06	0	1
## Rep_vote80975	-1.762e-05	4.541e+06	0	1
## Rep_vote81079	5.557e-08	2.738e+06	0	1
## Rep_vote81413	NA	NA	NA	NA
## Rep_vote81965	-1.844e-05	3.622e+06	0	1
## Rep_vote82793	8.921e-08	3.061e+06	0	1
## Rep_vote83769	8.267e-08	2.371e+06	0	1
## Rep_vote84475	NA	NA	NA	NA
## Rep_vote86077	-1.761e-05	2.738e+06	0	1
## Rep_vote86763	9.230e-09	3.353e+06	0	1
## Rep_vote87321	8.659e-07	2.738e+06	0	1
## Rep_vote87578	8.407e-07	3.622e+06	0	1
## Rep_vote87690	NA	NA	NA	NA
## Rep_vote88157	NA	NA	NA	NA
## Rep_vote88433	5.713e+01	1.936e+06	0	1
## Rep_vote89105	5.713e+01	2.371e+06	0	1
## Rep_vote89126	NA	NA	NA	NA
## Rep_vote89209	8.572e-07	2.738e+06	0	1
## Rep_vote89858	5.713e+01	4.936e+06	0	1
## Rep_vote89985	NA	NA	NA	NA
## Rep_vote90163	2.423e-09	3.061e+06	0	1
## Rep_vote90243	5.713e+01	2.371e+06	0	1
## Rep_vote90738	8.609e-07	3.061e+06	0	1
## Rep_vote91122	-4.065e-09	3.061e+06	0	1
## Rep_vote91780	2.106e-08	1.936e+06	0	1
## Rep_vote93463	-1.841e-05	2.738e+06	0	1
## Rep_vote93564	6.097e-08	3.872e+06	0	1
## Rep_vote93648	3.676e-08	3.061e+06	0	1
## Rep_vote94588	9.426e-08	3.353e+06	0	1
## Rep_vote94960	-3.392e-13	3.061e+06	0	1
## Rep_vote95385	1.032e-07	4.107e+06	0	1
## Rep_vote95482	-1.761e-05	3.622e+06	0	1
## Rep_vote96042	5.713e+01	2.738e+06	0	1
## Rep_vote96465	5.713e+01	3.061e+06	0	1
## Rep_vote96848	NA	NA	NA	NA
## Rep_vote97465	NA	NA	NA	NA
## Rep_vote97745	5.713e+01	2.738e+06	0	1
## Rep_vote98937	NA	NA	NA	NA
## Rep_vote99179	2.467e-13	2.738e+06	0	1
## Rep_vote99540	-1.763e-05	3.353e+06	0	1
## Rep_vote99631	-1.537e-13	4.742e+06	0	1
## Rep_vote100185	NA	NA	NA	NA
## Rep_vote101572	NA	NA	NA	NA
## Rep_vote102327	8.556e-07	3.061e+06	0	1

## Rep_vote102846	-1.843e-05	3.061e+06	0	1
## Rep_vote103458	4.347e-14	1.936e+06	0	1
## Rep_vote105506	-5.713e+01	3.622e+06	0	1
## Rep_vote105575	NA	NA	NA	NA
## Rep_vote105981	NA	NA	NA	NA
## Rep_vote106907	9.827e-08	3.622e+06	0	1
## Rep_vote106951	3.453e-13	3.061e+06	0	1
## Rep_vote107457	4.806e-08	2.738e+06	0	1
## Rep_vote107479	9.213e-08	2.738e+06	0	1
## Rep_vote107599	-2.168e-13	2.738e+06	0	1
## Rep_vote108373	8.519e-07	3.622e+06	0	1
## Rep_vote108763	5.713e+01	2.738e+06	0	1
## Rep_vote109193	5.713e+01	4.936e+06	0	1
## Rep_vote110169	NA	NA	NA	NA
## Rep_vote111125	-1.843e-05	3.622e+06	0	1
## Rep_vote111489	2.880e-13	3.061e+06	0	1
## Rep_vote112554	-4.599e-14	3.353e+06	0	1
## Rep_vote112746	3.299e-13	2.371e+06	0	1
## Rep_vote113068	1.670e-14	1.936e+06	0	1
## Rep_vote113543	8.107e-14	2.371e+06	0	1
## Rep_vote114458	-4.076e-13	1.936e+06	0	1
## Rep_vote115173	NA	NA	NA	NA
## Rep_vote116026	-3.287e-13	3.353e+06	0	1
## Rep_vote116241	NA	NA	NA	NA
## Rep_vote116309	-1.187e-13	1.936e+06	0	1
## Rep_vote116534	-2.997e-13	1.936e+06	0	1
## Rep_vote117601	3.623e-13	1.936e+06	0	1
## Rep_vote117710	NA	NA	NA	NA
## Rep_vote117761	2.293e-13	2.371e+06	0	1
## Rep_vote118350	NA	NA	NA	NA
## Rep_vote119526	2.862e-13	2.371e+06	0	1
## Rep_vote119742	-1.720e-13	3.061e+06	0	1
## Rep_vote120070	4.330e-14	3.622e+06	0	1
## Rep_vote120595	NA	NA	NA	NA
## Rep_vote121396	-1.144e-13	1.936e+06	0	1
## Rep_vote123838	-9.468e-14	3.872e+06	0	1
## Rep_vote124928	NA	NA	NA	NA
## Rep_vote125366	NA	NA	NA	NA
## Rep_vote125608	-5.713e+01	3.622e+06	0	1
## Rep_vote125733	1.022e-13	3.061e+06	0	1
## Rep_vote125859	NA	NA	NA	NA
## Rep_vote127722	-1.655e-13	1.936e+06	0	1
## Rep_vote127939	2.808e-13	3.353e+06	0	1
## Rep_vote128365	2.251e-13	2.371e+06	0	1
## Rep_vote128898	-3.364e-13	2.738e+06	0	1
## Rep_vote129085	-2.470e-14	2.371e+06	0	1
## Rep_vote129568	NA	NA	NA	NA
## Rep_vote129951	-1.666e-13	1.936e+06	0	1
## Rep_vote130578	9.377e-14	1.936e+06	0	1
## Rep_vote130893	NA	NA	NA	NA
## Rep_vote131043	-2.367e-13	2.738e+06	0	1
## Rep_vote131639	-3.738e-13	2.738e+06	0	1
## Rep_vote131824	NA	NA	NA	NA
## Rep_vote132090	-7.262e-14	3.353e+06	0	1

## Rep_vote132270	1.712e-13	2.738e+06	0	1
## Rep_vote132608	NA	NA	NA	NA
## Rep_vote132843	-2.770e-13	2.738e+06	0	1
## Rep_vote134881	-7.132e-14	1.936e+06	0	1
## Rep_vote135221	NA	NA	NA	NA
## Rep_vote135415	-3.005e-13	2.738e+06	0	1
## Rep_vote135883	2.696e-13	2.371e+06	0	1
## Rep_vote135937	3.933e-14	2.738e+06	0	1
## Rep_vote136384	-2.451e-13	4.107e+06	0	1
## Rep_vote136487	-1.770e-14	2.371e+06	0	1
## Rep_vote136944	2.713e-13	3.061e+06	0	1
## Rep_vote139010	-4.326e-13	3.622e+06	0	1
## Rep_vote139014	NA	NA	NA	NA
## Rep_vote139182	NA	NA	NA	NA
## Rep_vote140096	-6.343e-14	3.061e+06	0	1
## Rep_vote140171	6.112e-14	2.371e+06	0	1
## Rep_vote141832	3.795e-13	5.476e+06	0	1
## Rep_vote142025	NA	NA	NA	NA
## Rep_vote142597	-9.806e-14	2.738e+06	0	1
## Rep_vote142635	5.713e+01	1.936e+06	0	1
## Rep_vote142938	2.657e-13	3.061e+06	0	1
## Rep_vote143673	-1.485e-13	2.371e+06	0	1
## Rep_vote144227	-1.779e-13	3.061e+06	0	1
## Rep_vote145218	NA	NA	NA	NA
## Rep_vote145381	NA	NA	NA	NA
## Rep_vote145609	NA	NA	NA	NA
## Rep_vote146231	5.884e-14	1.936e+06	0	1
## Rep_vote146854	NA	NA	NA	NA
## Rep_vote147843	-1.799e-13	1.936e+06	0	1
## Rep_vote149748	4.901e-14	3.353e+06	0	1
## Rep_vote150223	NA	NA	NA	NA
## Rep_vote150443	1.783e-13	4.742e+06	0	1
## Rep_vote151038	NA	NA	NA	NA
## Rep_vote151704	NA	NA	NA	NA
## Rep_vote152191	2.557e-13	2.738e+06	0	1
## Rep_vote152235	-3.472e-13	2.738e+06	0	1
## Rep_vote152265	2.960e-13	2.738e+06	0	1
## Rep_vote152646	NA	NA	NA	NA
## Rep_vote153162	-5.860e-13	3.353e+06	0	1
## Rep_vote153280	NA	NA	NA	NA
## Rep_vote153350	-4.603e-13	2.371e+06	0	1
## Rep_vote153425	-1.331e-13	2.738e+06	0	1
## Rep_vote153453	1.815e-13	2.371e+06	0	1
## Rep_vote154164	-1.159e-13	3.061e+06	0	1
## Rep_vote154654	NA	NA	NA	NA
## Rep_vote154727	NA	NA	NA	NA
## Rep_vote154761	2.040e-14	3.353e+06	0	1
## Rep_vote155283	6.301e-13	1.936e+06	0	1
## Rep_vote155387	NA	NA	NA	NA
## Rep_vote156202	NA	NA	NA	NA
## Rep_vote156563	6.361e-14	3.353e+06	0	1
## Rep_vote157020	-4.294e-13	2.371e+06	0	1
## Rep_vote157513	3.046e-14	1.936e+06	0	1
## Rep_vote157956	NA	NA	NA	NA

```

## Rep_vote158519      NA      NA      NA      NA
## Rep_vote158824      NA      NA      NA      NA
## Rep_vote161146      NA      NA      NA      NA
## Rep_vote161623      NA      NA      NA      NA
## Rep_vote162779      NA      NA      NA      NA
## Rep_vote162962      NA      NA      NA      NA
## Rep_vote163729      NA      NA      NA      NA
## Rep_vote164462      NA      NA      NA      NA
## Rep_vote164692      NA      NA      NA      NA
## Rep_vote164699      NA      NA      NA      NA
## Rep_vote165913 -3.652e-14  1.936e+06      0      1
## Rep_vote165918      NA      NA      NA      NA
## Rep_vote165923      NA      NA      NA      NA
## Rep_vote166451      NA      NA      NA      NA
## Rep_vote166569 -5.713e+01  1.936e+06      0      1
## Rep_vote167229      NA      NA      NA      NA
## Rep_vote167275      NA      NA      NA      NA
## Rep_vote167470      NA      NA      NA      NA
## Rep_vote169165      NA      NA      NA      NA
## Rep_vote169360      NA      NA      NA      NA
## Rep_vote170302      NA      NA      NA      NA
## Rep_vote172619      NA      NA      NA      NA
## Rep_vote172992      NA      NA      NA      NA
## Rep_vote173876      NA      NA      NA      NA
## Rep_vote174284      NA      NA      NA      NA
## Rep_vote174453      NA      NA      NA      NA
## Rep_vote174942      NA      NA      NA      NA
## Rep_vote175562      NA      NA      NA      NA
## Rep_vote181203      NA      NA      NA      NA
## Rep_vote181269      NA      NA      NA      NA
## Rep_vote181413      NA      NA      NA      NA
## Rep_vote181612      NA      NA      NA      NA
## Rep_vote184639      NA      NA      NA      NA
## Rep_vote185093      NA      NA      NA      NA
## Rep_vote185203      NA      NA      NA      NA
## Rep_vote186356      NA      NA      NA      NA
## Rep_vote186450      NA      NA      NA      NA
## Rep_vote187380      NA      NA      NA      NA
## Rep_vote187850      NA      NA      NA      NA
## Rep_vote192064      NA      NA      NA      NA
## Rep_vote194944      NA      NA      NA      NA
## Rep_vote195579      NA      NA      NA      NA
## Rep_vote202478      NA      NA      NA      NA
## Rep_vote215322      NA      NA      NA      NA
## Rep_vote227882      NA      NA      NA      NA
## Rep_vote231170      NA      NA      NA      NA
##
## (Dispersion parameter for binomial family taken to be 1)
##
## Null deviance: 4.7827e+02 on 347 degrees of freedom
## Residual deviance: 2.7323e-10 on 0 degrees of freedom
## AIC: 696
##
## Number of Fisher Scoring iterations: 27

```

```
fit2<-glm(Dem_pct~x1+x2+incumbent+Rep_vote,data=data1,family=binomial(link="probit"),control=list(maxit=
summary(fit2)
```

```
##
## Call:
## glm(formula = Dem_pct ~ x1 + x2 + incumbent + Rep_vote, family = binomial(link = "probit"),
##      data = data1, control = list(maxit = 100))
##
## Deviance Residuals:
##      [1]  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
##     [24]  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
##     [47]  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
##     [70]  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
##     [93]  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
##    [116]  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
##    [139]  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
##    [162]  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
##    [185]  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
##    [208]  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
##    [231]  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
##    [254]  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
##    [277]  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
##    [300]  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
##    [323]  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
##    [346]  0  0  0
##
## Coefficients: (96 not defined because of singularities)
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -7.131e+00  2.081e+05      0      1
## x12           -3.927e-13  3.800e+05      0      1
## x13           -3.211e-13  2.403e+05      0      1
## x14           -2.505e-13  2.403e+05      0      1
## x15           -4.180e-13  3.800e+05      0      1
## x16           -2.933e-13  4.807e+05      0      1
## x111          -1.021e-05  3.399e+05      0      1
## x112          -3.200e-13  1.700e+05      0      1
## x113          -2.541e-13  2.403e+05      0      1
## x114          -2.124e-13  2.944e+05      0      1
## x121          -2.733e-13  2.403e+05      0      1
## x122          -2.338e-13  2.944e+05      0      1
## x123          -2.916e-13  2.944e+05      0      1
## x124          -3.768e-13  2.403e+05      0      1
## x125          -3.004e-13  2.944e+05      0      1
## x131          -2.578e-13  2.944e+05      0      1
## x132          -1.985e-13  2.403e+05      0      1
## x133          -2.203e-13  2.403e+05      0      1
## x134          -3.361e-13  3.800e+05      0      1
## x135          -2.594e-13  2.403e+05      0      1
## x136           4.297e-11  3.399e+05      0      1
## x137          -2.120e-08  3.399e+05      0      1
## x140          -2.619e-13  2.944e+05      0      1
## x141          -2.707e-13  2.403e+05      0      1
## x142          -3.018e-13  2.403e+05      0      1
## x143          -3.294e-13  3.399e+05      0      1
```

## x144	-2.675e-13	2.944e+05	0	1
## x145	-3.286e-13	3.399e+05	0	1
## x146	-3.462e-13	4.163e+05	0	1
## x147	-2.797e-13	3.399e+05	0	1
## x148	-2.593e-13	2.403e+05	0	1
## x149	-2.505e-13	2.403e+05	0	1
## x151	-2.634e-13	2.403e+05	0	1
## x152	-3.355e-13	3.399e+05	0	1
## x153	-2.569e-13	1.700e+05	0	1
## x154	-2.514e-13	2.944e+05	0	1
## x156	-1.021e-05	3.399e+05	0	1
## x161	-2.509e-13	1.700e+05	0	1
## x162	-2.871e-13	1.700e+05	0	1
## x163	-2.799e-13	2.403e+05	0	1
## x164	-2.944e-13	3.800e+05	0	1
## x165	-3.675e-13	3.800e+05	0	1
## x166	-3.407e-13	4.807e+05	0	1
## x167	-3.122e-13	2.403e+05	0	1
## x168	-8.598e-14	2.403e+05	0	1
## x171	-2.652e-13	2.944e+05	0	1
## x172	-3.155e-13	3.800e+05	0	1
## x173	-3.313e-13	3.399e+05	0	1
## x181	-2.072e-13	2.403e+05	0	1
## x182	-2.515e-13	2.403e+05	0	1
## x22	6.365e-14	3.399e+05	0	1
## x23	-2.827e-14	1.700e+05	0	1
## x24	5.398e-14	2.403e+05	0	1
## x25	1.831e-14	1.700e+05	0	1
## x26	1.477e-15	2.403e+05	0	1
## x27	-9.164e-15	2.403e+05	0	1
## x28	5.106e-14	2.944e+05	0	1
## x29	8.139e-14	2.944e+05	0	1
## x210	3.977e-14	2.944e+05	0	1
## x211	3.841e-14	2.403e+05	0	1
## x212	1.472e-13	2.403e+05	0	1
## x213	1.877e-14	2.403e+05	0	1
## x214	2.234e-14	2.944e+05	0	1
## x215	1.162e-13	2.944e+05	0	1
## x216	1.123e-13	2.944e+05	0	1
## x217	1.834e-14	3.399e+05	0	1
## x218	5.261e-14	3.399e+05	0	1
## x219	-4.790e-14	2.944e+05	0	1
## x220	2.948e-14	3.399e+05	0	1
## x221	-2.499e-14	5.887e+05	0	1
## x222	1.831e-14	3.399e+05	0	1
## x223	1.229e-14	2.944e+05	0	1
## x224	4.236e-14	2.944e+05	0	1
## x225	-3.043e-06	3.399e+05	0	1
## x226	2.941e-14	2.403e+05	0	1
## x227	-6.685e-14	5.099e+05	0	1
## x228	-7.173e-09	3.800e+05	0	1
## x229	2.725e-14	2.944e+05	0	1
## x230	-3.042e-06	3.800e+05	0	1
## x231	-6.598e-14	5.099e+05	0	1

## x232	1.069e-09	3.800e+05	0	1
## x233	2.018e-14	3.399e+05	0	1
## x234	-4.904e-09	3.800e+05	0	1
## x235	-1.130e-15	3.399e+05	0	1
## x236	-2.611e-09	3.800e+05	0	1
## x237	2.085e-16	3.399e+05	0	1
## x238	-1.426e+01	3.800e+05	0	1
## x239	-3.101e-14	3.399e+05	0	1
## x240	-3.875e-14	5.887e+05	0	1
## x241	1.577e-14	3.399e+05	0	1
## x242	-1.004e-13	5.887e+05	0	1
## x243	1.111e-14	3.399e+05	0	1
## x244	3.546e-09	3.800e+05	0	1
## x245	4.311e-14	3.399e+05	0	1
## x298	NA	NA	NA	NA
## incumbent0	6.797e-14	3.800e+05	0	1
## incumbent1	1.426e+01	2.403e+05	0	1
## Rep_vote13848	1.426e+01	4.163e+05	0	1
## Rep_vote14543	-1.021e-05	4.163e+05	0	1
## Rep_vote20729	-6.250e-09	4.496e+05	0	1
## Rep_vote24313	-1.021e-05	4.807e+05	0	1
## Rep_vote24804	-1.925e-09	6.128e+05	0	1
## Rep_vote27536	-1.021e-05	3.800e+05	0	1
## Rep_vote28645	NA	NA	NA	NA
## Rep_vote28831	2.916e-09	4.496e+05	0	1
## Rep_vote29156	3.615e-09	4.807e+05	0	1
## Rep_vote30944	-1.021e-05	4.496e+05	0	1
## Rep_vote33475	-1.022e-05	4.163e+05	0	1
## Rep_vote33692	-2.430e-09	3.399e+05	0	1
## Rep_vote34659	-1.021e-05	4.163e+05	0	1
## Rep_vote34909	-1.972e-09	4.163e+05	0	1
## Rep_vote36017	4.629e-09	5.099e+05	0	1
## Rep_vote36183	-1.022e-05	4.496e+05	0	1
## Rep_vote36309	-1.019e-05	4.163e+05	0	1
## Rep_vote36719	-1.021e-05	4.807e+05	0	1
## Rep_vote36801	-1.020e-05	4.807e+05	0	1
## Rep_vote36835	-1.021e-05	4.163e+05	0	1
## Rep_vote37454	1.426e+01	6.128e+05	0	1
## Rep_vote37693	-1.905e-08	3.800e+05	0	1
## Rep_vote37958	1.962e-11	3.800e+05	0	1
## Rep_vote38033	-1.021e-05	3.399e+05	0	1
## Rep_vote38381	-1.115e-08	4.807e+05	0	1
## Rep_vote39749	-1.021e-05	3.800e+05	0	1
## Rep_vote40277	-6.325e-09	3.800e+05	0	1
## Rep_vote40316	-5.659e-09	4.163e+05	0	1
## Rep_vote40732	1.019e-05	2.944e+05	0	1
## Rep_vote41076	-1.021e-05	3.800e+05	0	1
## Rep_vote41478	1.019e-05	2.944e+05	0	1
## Rep_vote42220	-1.020e-05	4.807e+05	0	1
## Rep_vote42664	4.819e-10	3.800e+05	0	1
## Rep_vote43833	3.033e-06	3.800e+05	0	1
## Rep_vote44043	NA	NA	NA	NA
## Rep_vote45239	-1.019e-05	3.800e+05	0	1
## Rep_vote45954	-4.469e-10	4.807e+05	0	1

## Rep_vote46130	-1.020e-05	5.099e+05	0	1
## Rep_vote46552	5.245e-09	3.800e+05	0	1
## Rep_vote46622	-1.022e-05	3.399e+05	0	1
## Rep_vote47039	-1.020e-05	5.099e+05	0	1
## Rep_vote47071	6.390e-09	3.399e+05	0	1
## Rep_vote47293	7.852e-10	3.800e+05	0	1
## Rep_vote47625	-1.020e-05	3.399e+05	0	1
## Rep_vote47929	5.509e-09	4.496e+05	0	1
## Rep_vote47957	-1.021e-05	3.800e+05	0	1
## Rep_vote48375	-1.021e-05	3.800e+05	0	1
## Rep_vote49498	-1.021e-05	4.163e+05	0	1
## Rep_vote49620	-1.021e-05	3.800e+05	0	1
## Rep_vote49657	-1.020e-05	4.163e+05	0	1
## Rep_vote49733	-1.021e-05	3.800e+05	0	1
## Rep_vote49753	NA	NA	NA	NA
## Rep_vote49855	-1.020e-05	3.800e+05	0	1
## Rep_vote50050	8.924e-10	3.399e+05	0	1
## Rep_vote50229	-2.557e-09	3.800e+05	0	1
## Rep_vote50356	2.163e-09	4.163e+05	0	1
## Rep_vote50710	NA	NA	NA	NA
## Rep_vote50954	NA	NA	NA	NA
## Rep_vote51628	5.208e-09	4.163e+05	0	1
## Rep_vote51985	-1.019e-05	3.399e+05	0	1
## Rep_vote52402	-1.021e-05	4.163e+05	0	1
## Rep_vote52807	-1.351e-08	3.800e+05	0	1
## Rep_vote53109	5.224e-09	4.496e+05	0	1
## Rep_vote53518	-1.022e-05	4.163e+05	0	1
## Rep_vote53588	-7.083e-10	4.496e+05	0	1
## Rep_vote53902	1.426e+01	3.800e+05	0	1
## Rep_vote54034	-1.021e-05	4.496e+05	0	1
## Rep_vote54195	3.755e-09	3.800e+05	0	1
## Rep_vote54528	-1.020e-05	3.399e+05	0	1
## Rep_vote55197	-5.535e-09	2.944e+05	0	1
## Rep_vote55511	NA	NA	NA	NA
## Rep_vote56630	6.771e-09	3.800e+05	0	1
## Rep_vote56656	3.494e-09	4.496e+05	0	1
## Rep_vote56893	1.426e+01	5.637e+05	0	1
## Rep_vote56963	-1.021e-05	2.944e+05	0	1
## Rep_vote57387	-1.020e-05	3.800e+05	0	1
## Rep_vote57587	-1.020e-05	3.399e+05	0	1
## Rep_vote57658	-1.019e-05	3.800e+05	0	1
## Rep_vote59128	-1.021e-05	2.944e+05	0	1
## Rep_vote59287	-1.022e-05	3.399e+05	0	1
## Rep_vote59688	-1.020e-05	4.496e+05	0	1
## Rep_vote59827	-1.035e-08	4.163e+05	0	1
## Rep_vote59877	-1.021e-05	3.399e+05	0	1
## Rep_vote59907	5.367e-09	4.807e+05	0	1
## Rep_vote60037	-3.331e-10	3.399e+05	0	1
## Rep_vote60346	-1.020e-05	3.399e+05	0	1
## Rep_vote60453	-1.022e-05	4.496e+05	0	1
## Rep_vote60559	-1.021e-05	3.399e+05	0	1
## Rep_vote60646	-1.021e-08	3.399e+05	0	1
## Rep_vote60946	-1.022e-05	3.399e+05	0	1
## Rep_vote62056	-1.018e-05	4.163e+05	0	1

## Rep_vote62564	-1.021e-05	4.496e+05	0	1
## Rep_vote63013	-4.380e-09	4.163e+05	0	1
## Rep_vote63372	4.744e-09	3.800e+05	0	1
## Rep_vote63959	-4.524e-09	2.944e+05	0	1
## Rep_vote64174	-1.021e-05	4.163e+05	0	1
## Rep_vote64491	-1.022e-05	3.399e+05	0	1
## Rep_vote64750	-1.021e-05	2.403e+05	0	1
## Rep_vote65278	-1.021e-05	3.399e+05	0	1
## Rep_vote65307	-1.775e-09	5.099e+05	0	1
## Rep_vote65393	-1.022e-05	4.807e+05	0	1
## Rep_vote65410	-1.021e-05	4.163e+05	0	1
## Rep_vote66521	-1.021e-05	5.099e+05	0	1
## Rep_vote66935	-1.021e-05	3.800e+05	0	1
## Rep_vote66972	-1.021e-05	4.807e+05	0	1
## Rep_vote67073	-1.022e-05	3.800e+05	0	1
## Rep_vote67337	-1.021e-05	3.800e+05	0	1
## Rep_vote67461	-1.021e-05	4.807e+05	0	1
## Rep_vote67604	-1.000e-08	4.163e+05	0	1
## Rep_vote67709	-1.021e-05	3.399e+05	0	1
## Rep_vote67759	-1.020e-05	4.496e+05	0	1
## Rep_vote68165	-1.020e-05	4.163e+05	0	1
## Rep_vote68226	5.130e-09	4.496e+05	0	1
## Rep_vote68363	3.489e-09	4.163e+05	0	1
## Rep_vote68788	-1.022e-05	3.800e+05	0	1
## Rep_vote68978	-1.021e-05	5.099e+05	0	1
## Rep_vote69165	6.941e-09	3.800e+05	0	1
## Rep_vote69303	-5.656e-09	3.399e+05	0	1
## Rep_vote70359	-1.020e-05	4.496e+05	0	1
## Rep_vote70534	-6.831e-10	4.163e+05	0	1
## Rep_vote71560	3.855e-09	3.399e+05	0	1
## Rep_vote71661	-1.022e-05	3.800e+05	0	1
## Rep_vote71905	-1.373e-08	3.399e+05	0	1
## Rep_vote72189	-1.723e-09	3.800e+05	0	1
## Rep_vote72489	-1.022e-05	2.944e+05	0	1
## Rep_vote73425	-3.568e-09	3.399e+05	0	1
## Rep_vote73659	-1.021e-05	4.496e+05	0	1
## Rep_vote73981	3.988e-09	4.163e+05	0	1
## Rep_vote74275	-1.021e-05	3.399e+05	0	1
## Rep_vote74296	-5.976e-09	3.800e+05	0	1
## Rep_vote74357	-1.021e-05	3.399e+05	0	1
## Rep_vote74405	-1.021e-05	4.496e+05	0	1
## Rep_vote74682	-1.022e-05	3.399e+05	0	1
## Rep_vote74824	-1.020e-05	3.800e+05	0	1
## Rep_vote75462	-1.021e-05	3.399e+05	0	1
## Rep_vote75571	-4.374e-09	3.399e+05	0	1
## Rep_vote76008	-3.522e-10	3.800e+05	0	1
## Rep_vote76179	NA	NA	NA	NA
## Rep_vote76531	-1.021e-05	4.496e+05	0	1
## Rep_vote77184	5.325e-10	4.496e+05	0	1
## Rep_vote77186	-1.022e-05	3.800e+05	0	1
## Rep_vote78028	-2.079e-09	3.399e+05	0	1
## Rep_vote78307	-1.021e-05	3.800e+05	0	1
## Rep_vote78396	-1.021e-05	2.944e+05	0	1
## Rep_vote78478	-1.021e-05	4.163e+05	0	1

## Rep_vote78626	-1.021e-05	4.496e+05	0	1
## Rep_vote78909	-1.021e-05	3.399e+05	0	1
## Rep_vote80181	-1.021e-05	3.399e+05	0	1
## Rep_vote80212	-1.020e-05	4.496e+05	0	1
## Rep_vote80372	-1.022e-05	3.399e+05	0	1
## Rep_vote80975	7.020e-09	5.637e+05	0	1
## Rep_vote81079	1.906e-09	3.399e+05	0	1
## Rep_vote81413	NA	NA	NA	NA
## Rep_vote81965	-1.021e-05	4.496e+05	0	1
## Rep_vote82793	8.596e-10	3.800e+05	0	1
## Rep_vote83769	-8.569e-09	2.944e+05	0	1
## Rep_vote84475	NA	NA	NA	NA
## Rep_vote86077	-1.021e-05	3.399e+05	0	1
## Rep_vote86763	-8.384e-09	4.163e+05	0	1
## Rep_vote87321	-1.019e-05	3.399e+05	0	1
## Rep_vote87578	-1.020e-05	4.496e+05	0	1
## Rep_vote87690	NA	NA	NA	NA
## Rep_vote88157	NA	NA	NA	NA
## Rep_vote88433	1.426e+01	2.403e+05	0	1
## Rep_vote89105	1.426e+01	2.944e+05	0	1
## Rep_vote89126	NA	NA	NA	NA
## Rep_vote89209	-1.316e-08	3.399e+05	0	1
## Rep_vote89858	1.426e+01	6.128e+05	0	1
## Rep_vote89985	NA	NA	NA	NA
## Rep_vote90163	-1.021e-05	3.800e+05	0	1
## Rep_vote90243	1.426e+01	2.944e+05	0	1
## Rep_vote90738	-1.022e-05	3.800e+05	0	1
## Rep_vote91122	-1.444e-09	3.800e+05	0	1
## Rep_vote91780	-1.021e-05	2.403e+05	0	1
## Rep_vote93463	-1.021e-05	3.399e+05	0	1
## Rep_vote93564	-1.021e-05	4.807e+05	0	1
## Rep_vote93648	-1.021e-05	3.800e+05	0	1
## Rep_vote94588	-1.021e-05	4.163e+05	0	1
## Rep_vote94960	-9.192e-14	3.800e+05	0	1
## Rep_vote95385	-1.021e-05	5.099e+05	0	1
## Rep_vote95482	-1.021e-05	4.496e+05	0	1
## Rep_vote96042	1.426e+01	3.399e+05	0	1
## Rep_vote96465	1.426e+01	3.800e+05	0	1
## Rep_vote96848	NA	NA	NA	NA
## Rep_vote97465	NA	NA	NA	NA
## Rep_vote97745	1.426e+01	3.399e+05	0	1
## Rep_vote98937	NA	NA	NA	NA
## Rep_vote99179	2.309e-14	3.399e+05	0	1
## Rep_vote99540	-1.021e-05	4.163e+05	0	1
## Rep_vote99631	-1.150e-13	5.887e+05	0	1
## Rep_vote100185	NA	NA	NA	NA
## Rep_vote101572	NA	NA	NA	NA
## Rep_vote102327	-1.022e-05	3.800e+05	0	1
## Rep_vote102846	-1.022e-05	3.800e+05	0	1
## Rep_vote103458	2.236e-14	2.403e+05	0	1
## Rep_vote105506	-1.426e+01	4.496e+05	0	1
## Rep_vote105575	NA	NA	NA	NA
## Rep_vote105981	NA	NA	NA	NA
## Rep_vote106907	-1.027e-08	4.496e+05	0	1

## Rep_vote106951	-1.501e-13	3.800e+05	0	1
## Rep_vote107457	-1.021e-05	3.399e+05	0	1
## Rep_vote107479	-1.022e-05	3.399e+05	0	1
## Rep_vote107599	-1.508e-13	3.399e+05	0	1
## Rep_vote108373	-3.131e-09	4.496e+05	0	1
## Rep_vote108763	1.426e+01	3.399e+05	0	1
## Rep_vote109193	1.426e+01	6.128e+05	0	1
## Rep_vote110169	NA	NA	NA	NA
## Rep_vote111125	1.117e-09	4.496e+05	0	1
## Rep_vote111489	6.450e-14	3.800e+05	0	1
## Rep_vote112554	-7.453e-15	4.163e+05	0	1
## Rep_vote112746	-1.237e-14	2.944e+05	0	1
## Rep_vote113068	7.735e-14	2.403e+05	0	1
## Rep_vote113543	-9.296e-14	2.944e+05	0	1
## Rep_vote114458	-6.121e-14	2.403e+05	0	1
## Rep_vote115173	NA	NA	NA	NA
## Rep_vote116026	7.132e-14	4.163e+05	0	1
## Rep_vote116241	NA	NA	NA	NA
## Rep_vote116309	-1.169e-14	2.403e+05	0	1
## Rep_vote116534	3.588e-14	2.403e+05	0	1
## Rep_vote117601	-3.329e-14	2.403e+05	0	1
## Rep_vote117710	NA	NA	NA	NA
## Rep_vote117761	-1.353e-14	2.944e+05	0	1
## Rep_vote118350	NA	NA	NA	NA
## Rep_vote119526	-1.551e-14	2.944e+05	0	1
## Rep_vote119742	-2.163e-14	3.800e+05	0	1
## Rep_vote120070	-4.261e-14	4.496e+05	0	1
## Rep_vote120595	NA	NA	NA	NA
## Rep_vote121396	-9.548e-14	2.403e+05	0	1
## Rep_vote123838	6.695e-14	4.807e+05	0	1
## Rep_vote124928	NA	NA	NA	NA
## Rep_vote125366	NA	NA	NA	NA
## Rep_vote125608	-1.426e+01	4.496e+05	0	1
## Rep_vote125733	-1.068e-14	3.800e+05	0	1
## Rep_vote125859	NA	NA	NA	NA
## Rep_vote127722	-8.935e-14	2.403e+05	0	1
## Rep_vote127939	-8.861e-15	4.163e+05	0	1
## Rep_vote128365	-1.088e-13	2.944e+05	0	1
## Rep_vote128898	5.561e-16	3.399e+05	0	1
## Rep_vote129085	-3.374e-14	2.944e+05	0	1
## Rep_vote129568	NA	NA	NA	NA
## Rep_vote129951	3.755e-14	2.403e+05	0	1
## Rep_vote130578	-4.647e-14	2.403e+05	0	1
## Rep_vote130893	NA	NA	NA	NA
## Rep_vote131043	9.125e-15	3.399e+05	0	1
## Rep_vote131639	-1.467e-13	3.399e+05	0	1
## Rep_vote131824	NA	NA	NA	NA
## Rep_vote132090	-3.736e-14	4.163e+05	0	1
## Rep_vote132270	-8.328e-14	3.399e+05	0	1
## Rep_vote132608	NA	NA	NA	NA
## Rep_vote132843	-2.569e-13	3.399e+05	0	1
## Rep_vote134881	9.856e-15	2.403e+05	0	1
## Rep_vote135221	NA	NA	NA	NA
## Rep_vote135415	4.395e-14	3.399e+05	0	1

## Rep_vote135883	5.731e-14	2.944e+05	0	1
## Rep_vote135937	-3.053e-14	3.399e+05	0	1
## Rep_vote136384	-9.563e-14	5.099e+05	0	1
## Rep_vote136487	3.586e-14	2.944e+05	0	1
## Rep_vote136944	-1.765e-13	3.800e+05	0	1
## Rep_vote139010	-5.460e-14	4.496e+05	0	1
## Rep_vote139014	NA	NA	NA	NA
## Rep_vote139182	NA	NA	NA	NA
## Rep_vote140096	-4.180e-14	3.800e+05	0	1
## Rep_vote140171	-4.617e-14	2.944e+05	0	1
## Rep_vote141832	-4.191e-14	6.798e+05	0	1
## Rep_vote142025	NA	NA	NA	NA
## Rep_vote142597	9.252e-14	3.399e+05	0	1
## Rep_vote142635	1.426e+01	2.403e+05	0	1
## Rep_vote142938	1.946e-14	3.800e+05	0	1
## Rep_vote143673	9.582e-14	2.944e+05	0	1
## Rep_vote144227	3.899e-14	3.800e+05	0	1
## Rep_vote145218	NA	NA	NA	NA
## Rep_vote145381	NA	NA	NA	NA
## Rep_vote145609	NA	NA	NA	NA
## Rep_vote146231	-5.624e-14	2.403e+05	0	1
## Rep_vote146854	NA	NA	NA	NA
## Rep_vote147843	-3.311e-13	2.403e+05	0	1
## Rep_vote149748	-4.124e-14	4.163e+05	0	1
## Rep_vote150223	NA	NA	NA	NA
## Rep_vote150443	6.979e-14	5.887e+05	0	1
## Rep_vote151038	NA	NA	NA	NA
## Rep_vote151704	NA	NA	NA	NA
## Rep_vote152191	-1.108e-13	3.399e+05	0	1
## Rep_vote152235	1.141e-13	3.399e+05	0	1
## Rep_vote152265	4.701e-14	3.399e+05	0	1
## Rep_vote152646	NA	NA	NA	NA
## Rep_vote153162	5.262e-14	4.163e+05	0	1
## Rep_vote153280	NA	NA	NA	NA
## Rep_vote153350	8.679e-14	2.944e+05	0	1
## Rep_vote153425	2.729e-14	3.399e+05	0	1
## Rep_vote153453	-8.246e-14	2.944e+05	0	1
## Rep_vote154164	2.371e-14	3.800e+05	0	1
## Rep_vote154654	NA	NA	NA	NA
## Rep_vote154727	NA	NA	NA	NA
## Rep_vote154761	-6.182e-14	4.163e+05	0	1
## Rep_vote155283	4.775e-15	2.403e+05	0	1
## Rep_vote155387	NA	NA	NA	NA
## Rep_vote156202	NA	NA	NA	NA
## Rep_vote156563	3.919e-14	4.163e+05	0	1
## Rep_vote157020	-2.641e-13	2.944e+05	0	1
## Rep_vote157513	4.967e-14	2.403e+05	0	1
## Rep_vote157956	NA	NA	NA	NA
## Rep_vote158519	NA	NA	NA	NA
## Rep_vote158824	NA	NA	NA	NA
## Rep_vote161146	NA	NA	NA	NA
## Rep_vote161623	NA	NA	NA	NA
## Rep_vote162779	NA	NA	NA	NA
## Rep_vote162962	NA	NA	NA	NA

```

## Rep_vote163729      NA      NA      NA      NA
## Rep_vote164462      NA      NA      NA      NA
## Rep_vote164692      NA      NA      NA      NA
## Rep_vote164699      NA      NA      NA      NA
## Rep_vote165913 -6.938e-14  2.403e+05      0      1
## Rep_vote165918      NA      NA      NA      NA
## Rep_vote165923      NA      NA      NA      NA
## Rep_vote166451      NA      NA      NA      NA
## Rep_vote166569 -1.426e+01  2.403e+05      0      1
## Rep_vote167229      NA      NA      NA      NA
## Rep_vote167275      NA      NA      NA      NA
## Rep_vote167470      NA      NA      NA      NA
## Rep_vote169165      NA      NA      NA      NA
## Rep_vote169360      NA      NA      NA      NA
## Rep_vote170302      NA      NA      NA      NA
## Rep_vote172619      NA      NA      NA      NA
## Rep_vote172992      NA      NA      NA      NA
## Rep_vote173876      NA      NA      NA      NA
## Rep_vote174284      NA      NA      NA      NA
## Rep_vote174453      NA      NA      NA      NA
## Rep_vote174942      NA      NA      NA      NA
## Rep_vote175562      NA      NA      NA      NA
## Rep_vote181203      NA      NA      NA      NA
## Rep_vote181269      NA      NA      NA      NA
## Rep_vote181413      NA      NA      NA      NA
## Rep_vote181612      NA      NA      NA      NA
## Rep_vote184639      NA      NA      NA      NA
## Rep_vote185093      NA      NA      NA      NA
## Rep_vote185203      NA      NA      NA      NA
## Rep_vote186356      NA      NA      NA      NA
## Rep_vote186450      NA      NA      NA      NA
## Rep_vote187380      NA      NA      NA      NA
## Rep_vote187850      NA      NA      NA      NA
## Rep_vote192064      NA      NA      NA      NA
## Rep_vote194944      NA      NA      NA      NA
## Rep_vote195579      NA      NA      NA      NA
## Rep_vote202478      NA      NA      NA      NA
## Rep_vote215322      NA      NA      NA      NA
## Rep_vote227882      NA      NA      NA      NA
## Rep_vote231170      NA      NA      NA      NA
##
## (Dispersion parameter for binomial family taken to be 1)
##
## Null deviance: 4.7827e+02 on 347 degrees of freedom
## Residual deviance: 3.4556e-10 on 0 degrees of freedom
## AIC: 696
##
## Number of Fisher Scoring iterations: 26

```

2. Fit a robit regression and assess model fit.

3. Which model do you prefer?

Salmonella

The `salmonella` data was collected in a salmonella reverse mutagenicity assay. The predictor is the dose level of quinoline and the response is the numbers of revertant colonies of TA98 salmonella observed on each of three replicate plates. Show that a Poisson GLM is inadequate and that some overdispersion must be allowed for. Do not forget to check out other reasons for a high deviance.

```
data(salmonella)
?salmonella
mod_sal<- glm(colonies ~ dose, data = salmonella, family = poisson)
summary(mod_sal)
```

```
##
## Call:
## glm(formula = colonies ~ dose, family = poisson, data = salmonella)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -2.6482  -1.8225  -0.2993   1.2917   5.1861
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)  3.3219950  0.0540292   61.485  <2e-16 ***
## dose          0.0001901  0.0001172    1.622    0.105
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
##
##      Null deviance: 78.358  on 17  degrees of freedom
## Residual deviance: 75.806  on 16  degrees of freedom
## AIC: 172.34
##
## Number of Fisher Scoring iterations: 4
```

```
tapply(salmonella$dose, salmonella$colonies,
       function(x)c(mean=mean(x),variance=var(x)))
```

```
## $`15`
##      mean variance
##         0        NA
##
## $`16`
##      mean variance
##     21.5     264.5
##
## $`18`
##      mean variance
##        10        NA
##
## $`20`
##      mean variance
##     1000         NA
##
## $`21`
```



```
##      mean variance
##      5         50
##
## $`26`
##      mean variance
##      33         NA
##
## $`27`
##      mean variance
##      550      405000
##
## $`29`
##      mean variance
##      0         NA
##
## $`33`
##      mean variance
##      183      45000
##
## $`38`
##      mean variance
##      333         NA
##
## $`41`
##      mean variance
##      216.5    27144.5
##
## $`42`
##      mean variance
##      1000         NA
##
## $`60`
##      mean variance
##      100         NA

# The data is overdispersion because its variance is so many times of its mean.
mod_sal2<- glm(colonies ~ dose, data = salmonella, family = quasipoisson)
summary.glm(mod_sal2)
```

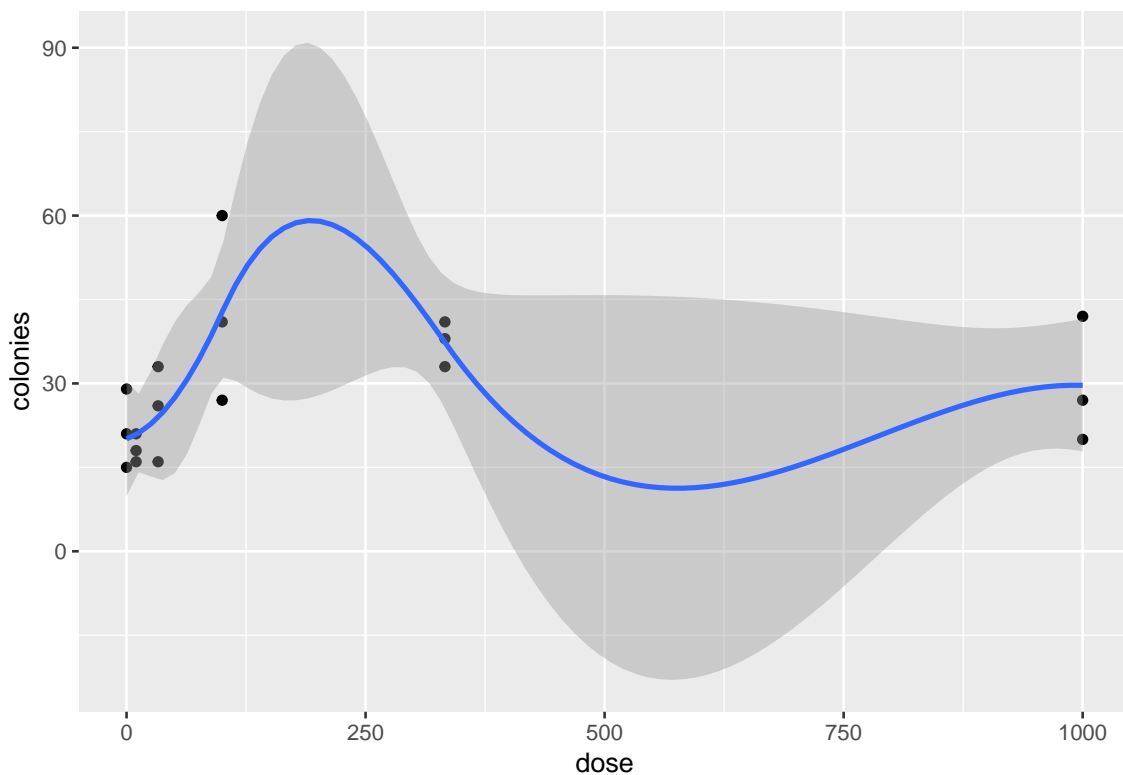
```
##
## Call:
## glm(formula = colonies ~ dose, family = quasipoisson, data = salmonella)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -2.6482  -1.8225  -0.2993   1.2917   5.1861
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  3.3219950  0.1218628  27.260 7.72e-15 ***
## dose          0.0001901  0.0002644   0.719   0.482
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for quasipoisson family taken to be 5.087279)
```

```
##
## Null deviance: 78.358 on 17 degrees of freedom
## Residual deviance: 75.806 on 16 degrees of freedom
## AIC: NA
##
## Number of Fisher Scoring iterations: 4
# The overdispersion factor is 5.09
```

When you plot the data you see that the number of colonies as a function of dose is not monotonic especially around the dose of 1000.

```
library(ggplot2)
ggplot(data=salmonella)+geom_point(mapping = aes(y=colonies,x=dose))+geom_smooth(mapping = aes(y=colonies,x=dose))

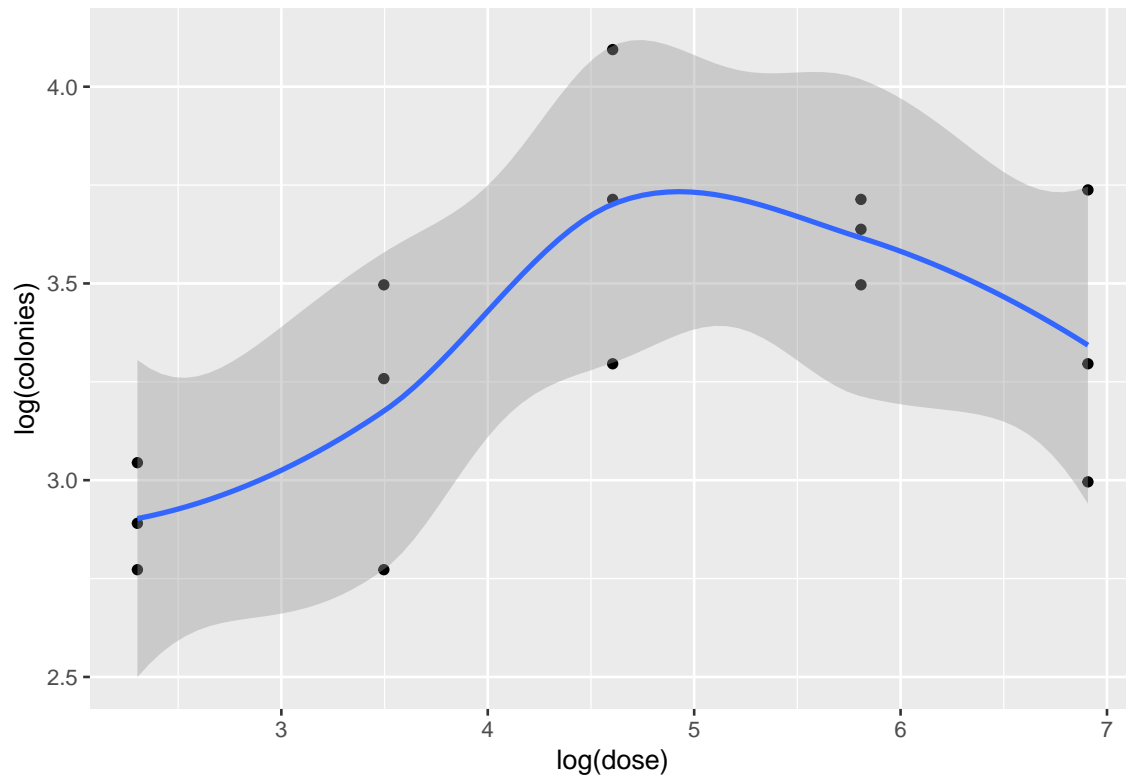
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```



Since we are fitting log linear model we should look at the data on log scale. Also because the dose is not equally spaced on the raw scale it may be better to plot it on the log scale as well.

```
data_sal<-filter(salmonella,dose!=0)
ggplot(data=data_sal)+geom_point(mapping = aes(y=log(colonies),x=log(dose)))+geom_smooth(mapping = aes(y=log(colonies),x=log(dose)))

## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```

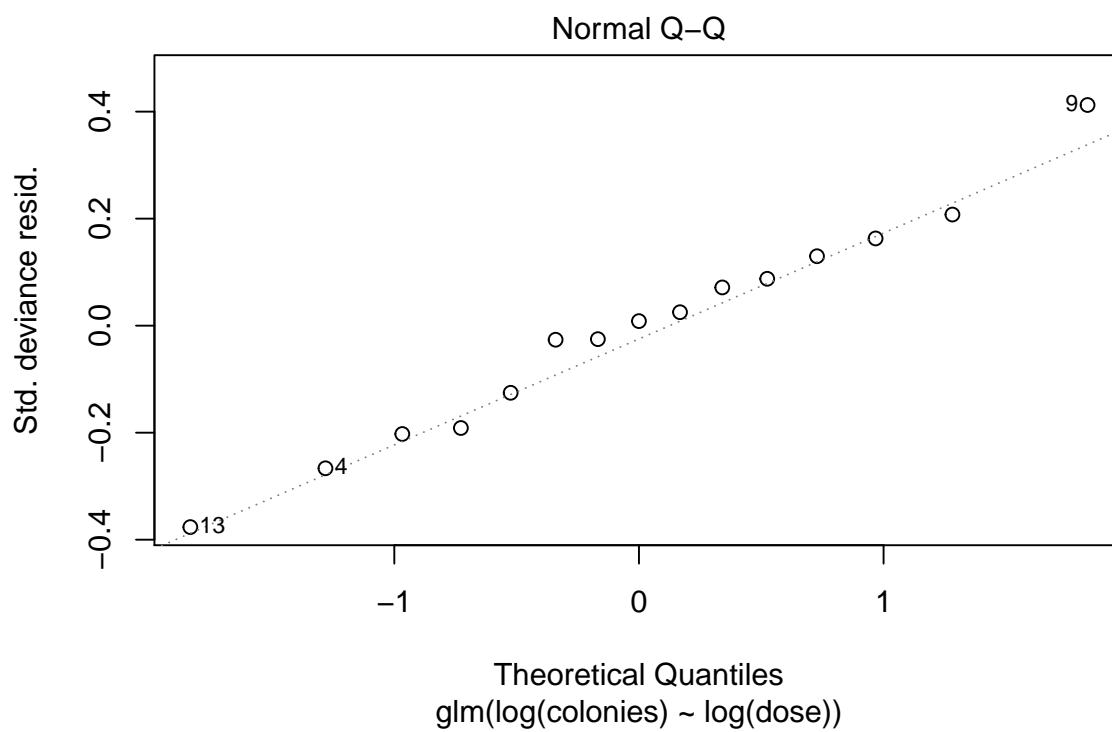
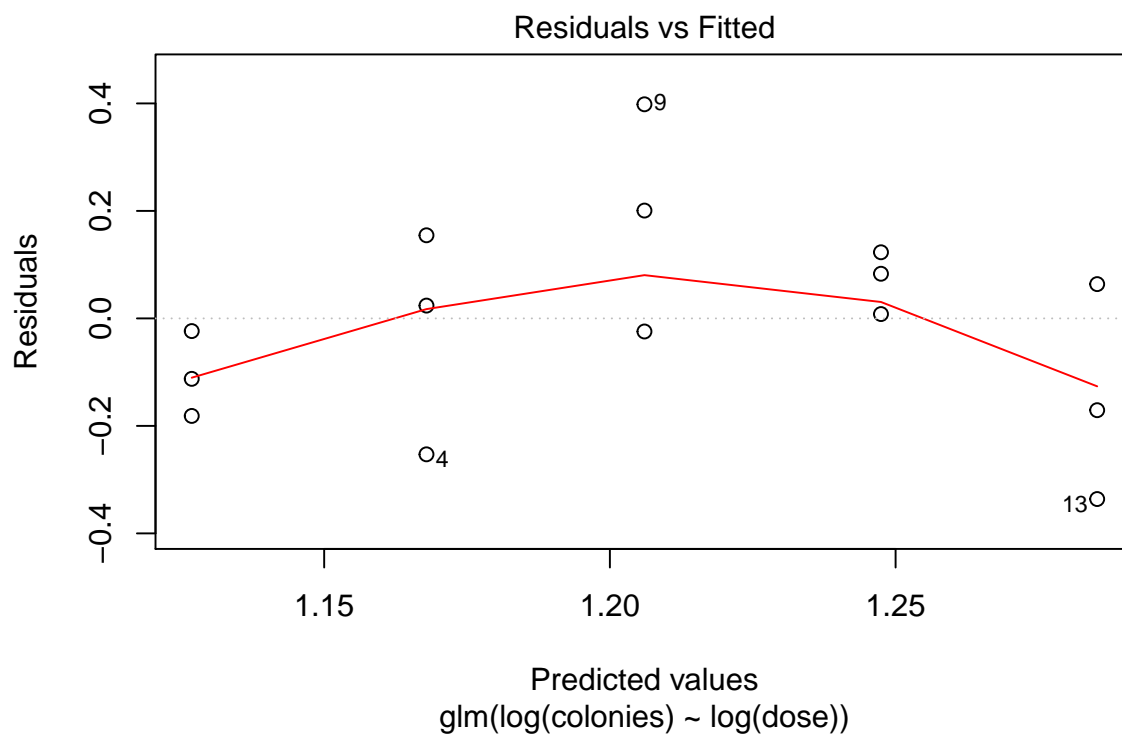


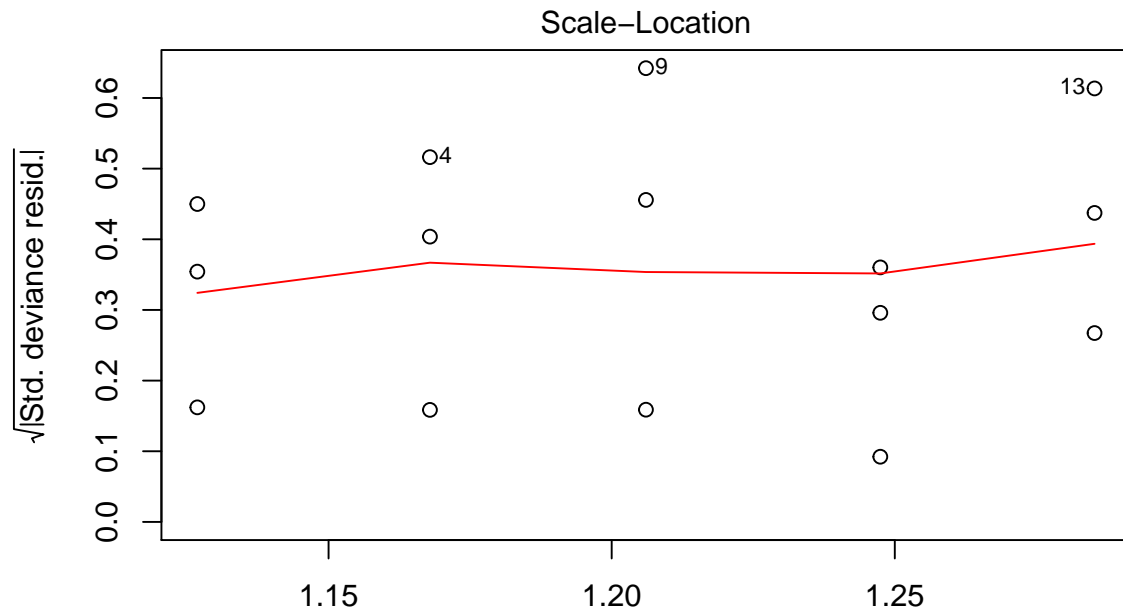
This shows that the trend is not monotonic. Hence when you fit the model and look at the residual you will see a trend.

```
mod_sal3<- glm(log(colonies) ~ log(dose), data = data_sal, family = poisson)
```

```
## Warning in dpois(y, mu, log = TRUE): non-integer x = 2.772589
## Warning in dpois(y, mu, log = TRUE): non-integer x = 2.890372
## Warning in dpois(y, mu, log = TRUE): non-integer x = 3.044522
## Warning in dpois(y, mu, log = TRUE): non-integer x = 2.772589
## Warning in dpois(y, mu, log = TRUE): non-integer x = 3.258097
## Warning in dpois(y, mu, log = TRUE): non-integer x = 3.496508
## Warning in dpois(y, mu, log = TRUE): non-integer x = 3.295837
## Warning in dpois(y, mu, log = TRUE): non-integer x = 3.713572
## Warning in dpois(y, mu, log = TRUE): non-integer x = 4.094345
## Warning in dpois(y, mu, log = TRUE): non-integer x = 3.496508
## Warning in dpois(y, mu, log = TRUE): non-integer x = 3.637586
## Warning in dpois(y, mu, log = TRUE): non-integer x = 3.713572
## Warning in dpois(y, mu, log = TRUE): non-integer x = 2.995732
## Warning in dpois(y, mu, log = TRUE): non-integer x = 3.295837
## Warning in dpois(y, mu, log = TRUE): non-integer x = 3.737670
```

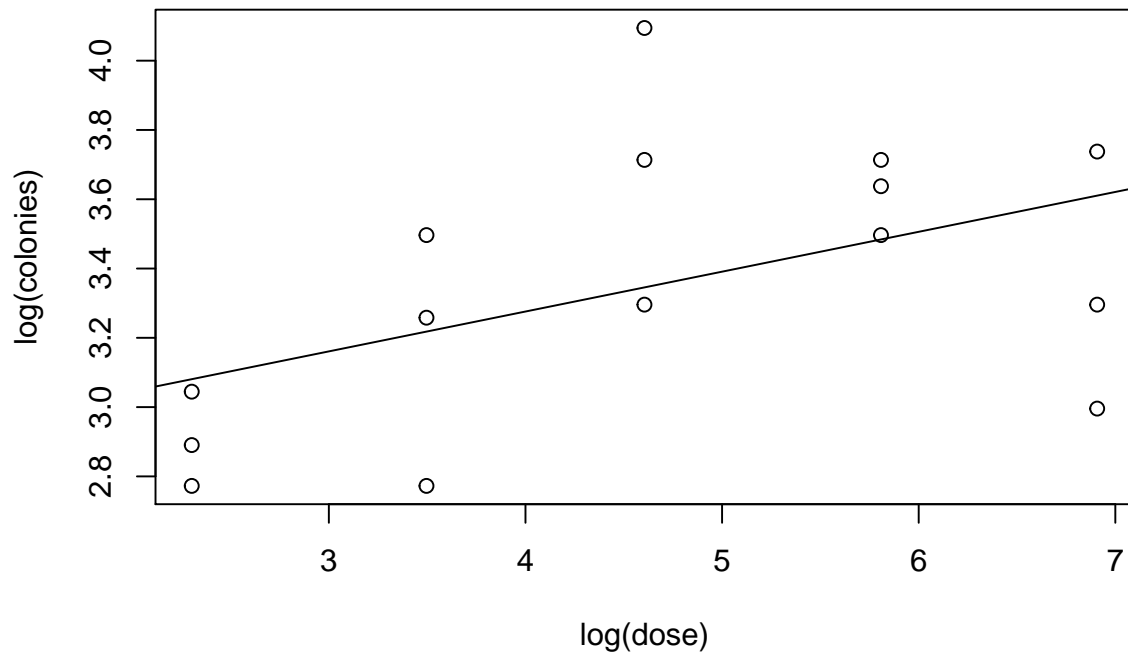
```
plot(mod_sal3)
```





The lack of fit is also evident if we plot the fitted line onto the data.

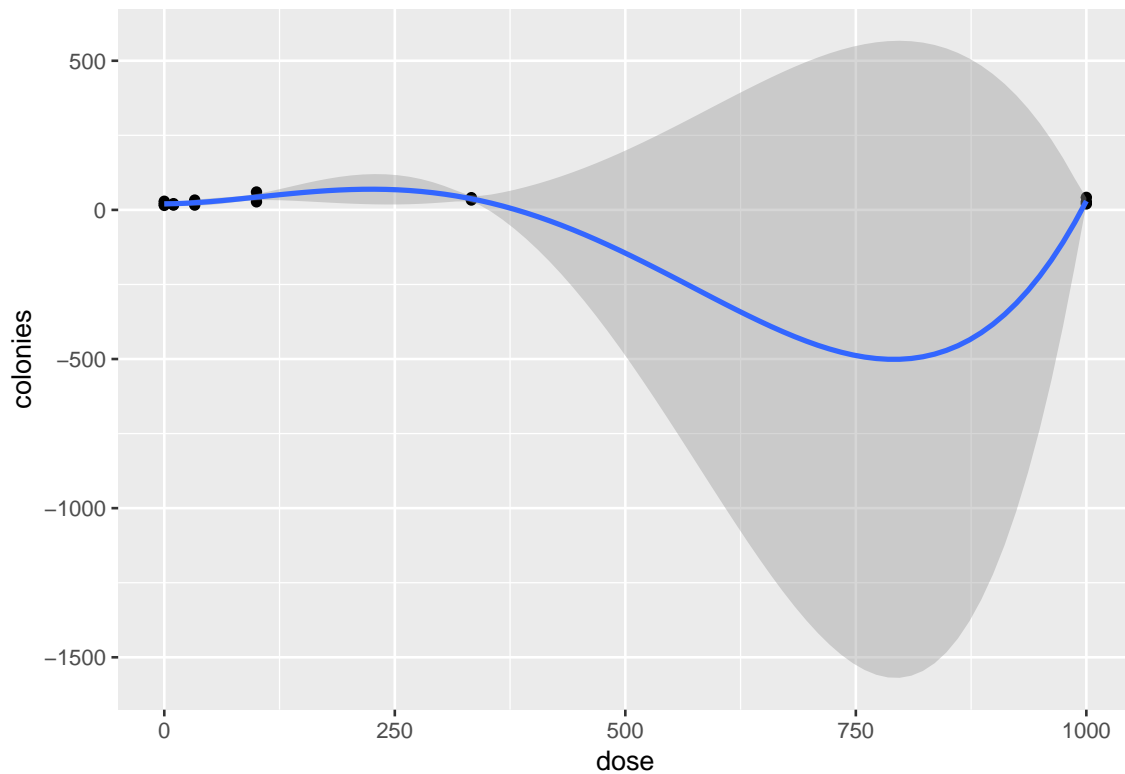
```
plot(x = log(data_sal$dose), y = log(data_sal$colonies), xlab = "log(dose)", ylab = "log(colonies)")
abline(lm(log(data_sal$colonies) ~ log(data_sal$dose)))
```



We can see that the fitted line has no intercepts with the scatter plot.

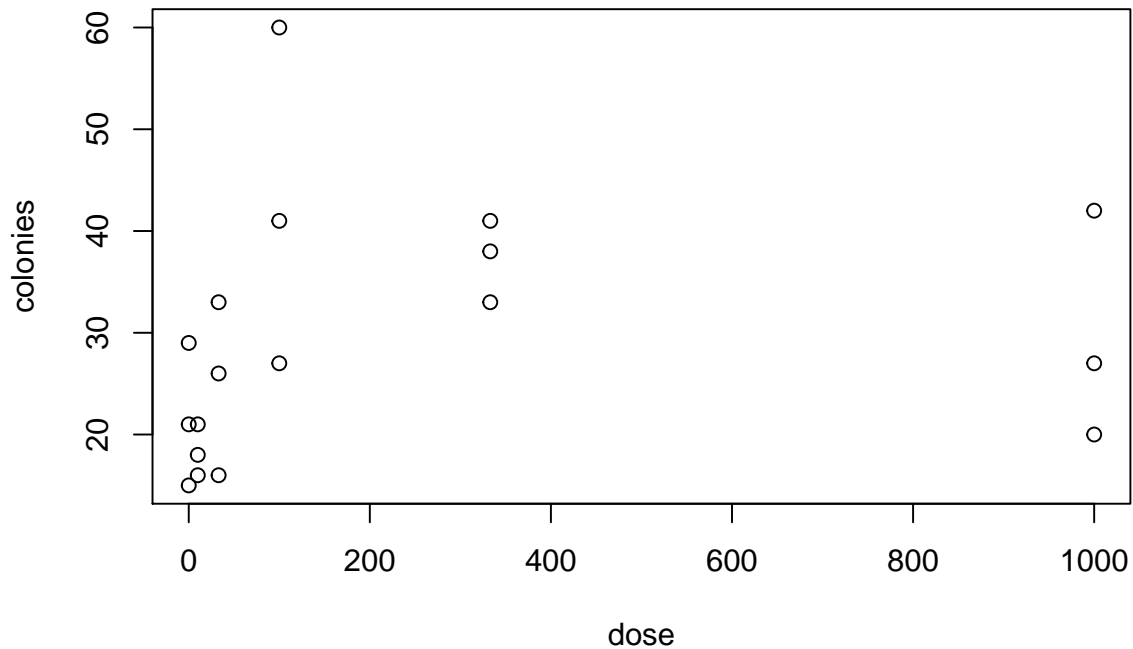
How do we address this problem? The serious problem to address is the nonlinear trend of dose rather than the overdispersion since the line is missing the points. Let's add a beny line with 4th order polynomial.

```
ggplot(data=salmonella)+geom_point(mapping = aes(y=colonies,x=dose))+geom_smooth(mapping = aes(y=colonies,x=dose))
```

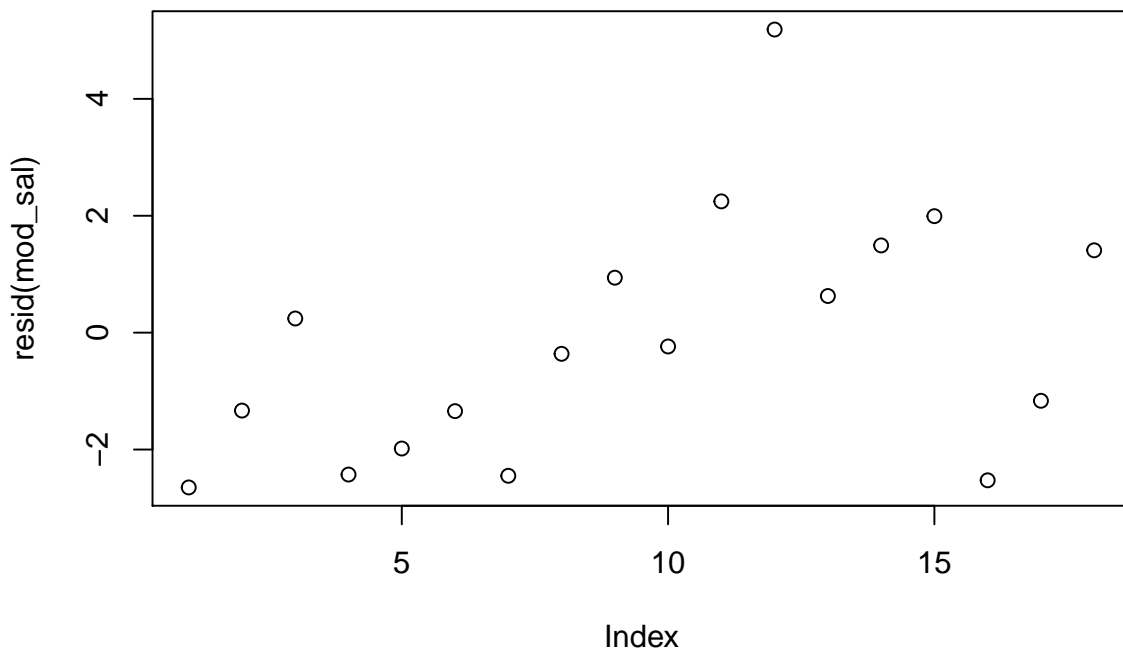


The resulting residual looks nice and if you plot it on the raw data. Whether the trend makes real contextual sense will need to be validated but for the given data it looks feasible.

```
plot(x = salmonella$dose, y =salmonella$colonies, xlab = "dose", ylab = "colonies")
```



```
plot(resid(mod_sal))
```



Dispite the fit, the overdispersion still exists so we'd be better off using the quasi Poisson model.

```
mod_sal3<- glm(colonies ~ dose, data = salmonella, family = quasipoisson)
summary.glm(mod_sal3)
```

```
##
## Call:
## glm(formula = colonies ~ dose, family = quasipoisson, data = salmonella)
##
```

```
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -2.6482  -1.8225  -0.2993   1.2917   5.1861
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  3.3219950  0.1218628  27.260 7.72e-15 ***
## dose         0.0001901  0.0002644   0.719   0.482
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for quasipoisson family taken to be 5.087279)
##
##      Null deviance: 78.358  on 17  degrees of freedom
## Residual deviance: 75.806  on 16  degrees of freedom
## AIC: NA
##
## Number of Fisher Scoring iterations: 4
```

Ships

The `ships` dataset found in the `MASS` package gives the number of damage incidents and aggregate months of service for different types of ships broken down by year of construction and period of operation.

```
data(ships)
?ships
```

Develop a model for the rate of incidents, describing the effect of the important predictors.

```
mod_ship<- glm(incidents ~ type+year+period+service, data = ships, family = poisson)
summary(mod_ship)
```

```
##
## Call:
## glm(formula = incidents ~ type + year + period + service, family = poisson,
##      data = ships)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -4.1013  -1.9648  -0.5380   0.9899   4.6212
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -5.706e+00  1.221e+00  -4.673 2.96e-06 ***
## typeB        8.135e-01  2.023e-01   4.021 5.79e-05 ***
## typeC       -1.205e+00  3.275e-01  -3.679 0.000234 ***
## typeD       -8.595e-01  2.875e-01  -2.989 0.002795 **
## typeE       -2.226e-01  2.348e-01  -0.948 0.343173
## year         4.519e-02  1.341e-02   3.370 0.000752 ***
## period       6.055e-02  8.945e-03   6.768 1.30e-11 ***
## service      5.970e-05  7.016e-06   8.509 < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```



```
## (Dispersion parameter for poisson family taken to be 1)
##
##      Null deviance: 730.25  on 39  degrees of freedom
## Residual deviance: 174.00  on 32  degrees of freedom
## AIC: 287.86
##
## Number of Fisher Scoring iterations: 6
# The predictor type has important effects, since four types all have relative large coefficients.
```

Australian Health Survey

The `dvisits` data comes from the Australian Health Survey of 1977-78 and consist of 5190 single adults where young and old have been oversampled.

```
data(dvisits)
?dvisits
```

1. Build a Poisson regression model with `doctorco` as the response and `sex`, `age`, `agesq`, `income`, `levyplus`, `freepoor`, `freerepa`, `illness`, `actdays`, `hscore`, `chcond1` and `chcond2` as possible predictor variables. Considering the deviance of this model, does this model fit the data?

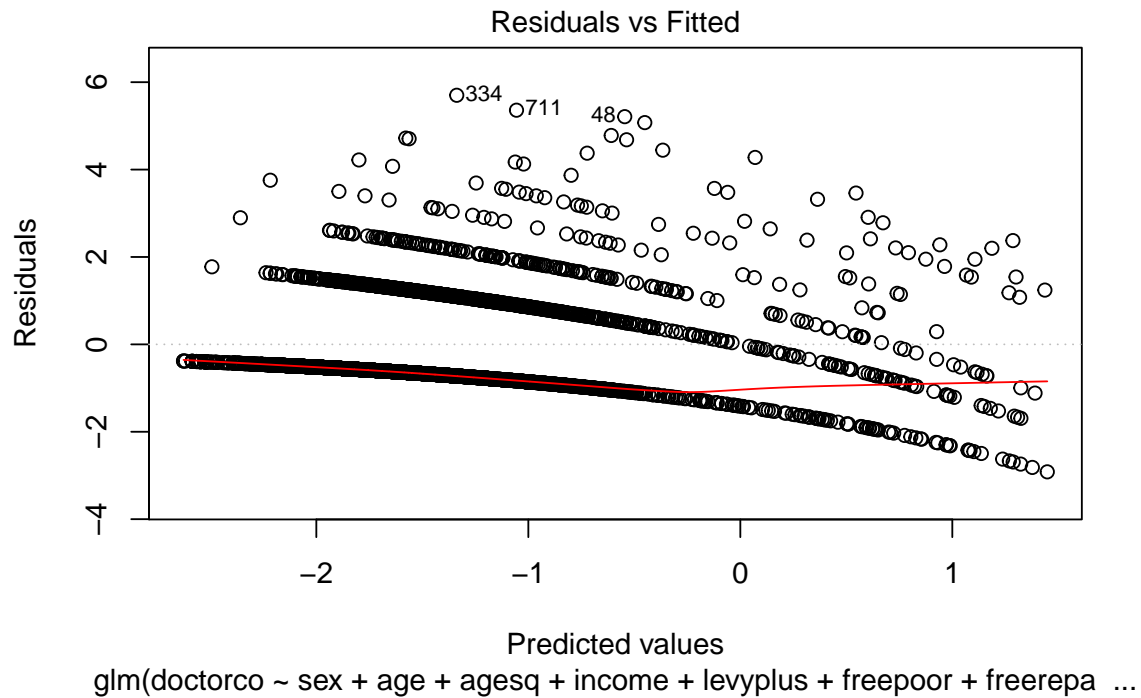
```
mod_dvis<-glm(doctorco ~ sex + age + agesq + income + levyplus + freepoor + freerepa + illness + actdays,
              data = dvisits, family = poisson)
summary(mod_dvis)
```

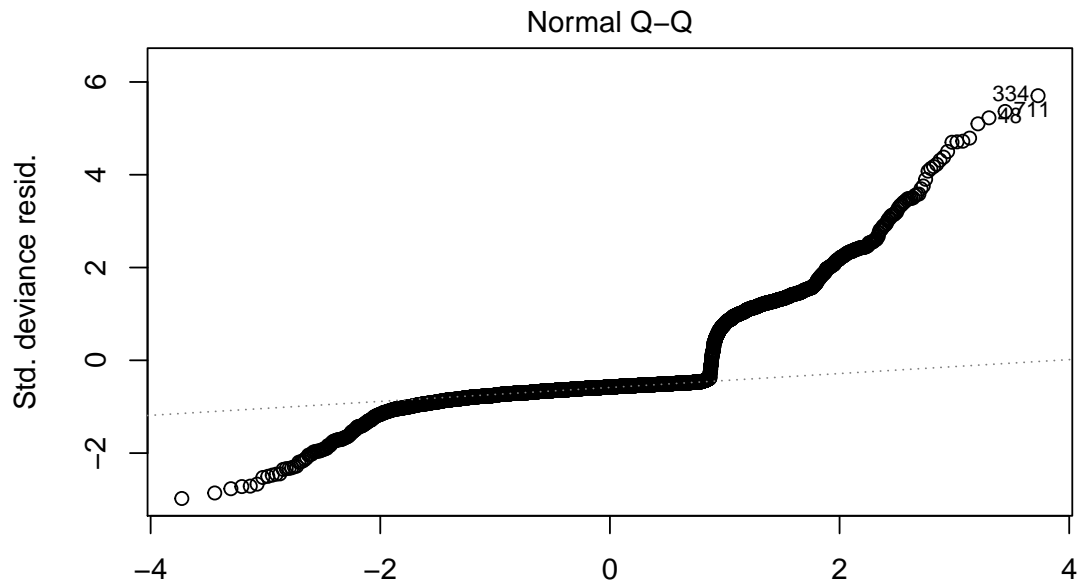
```
##
## Call:
## glm(formula = doctorco ~ sex + age + agesq + income + levyplus +
##      freepoor + freerepa + illness + actdays + hscore + chcond1 +
##      chcond2, family = poisson, data = dvisits)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -2.9170  -0.6862  -0.5743  -0.4839   5.7005
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -2.223848   0.189816 -11.716  <2e-16 ***
## sex          0.156882   0.056137   2.795   0.0052 **
## age          1.056299   1.000780   1.055   0.2912
## agesq       -0.848704   1.077784  -0.787   0.4310
## income      -0.205321   0.088379  -2.323   0.0202 *
## levyplus     0.123185   0.071640   1.720   0.0855 .
## freepoor    -0.440061   0.179811  -2.447   0.0144 *
## freerepa     0.079798   0.092060   0.867   0.3860
## illness     0.186948   0.018281  10.227  <2e-16 ***
## actdays     0.126846   0.005034  25.198  <2e-16 ***
## hscore       0.030081   0.010099   2.979   0.0029 **
## chcond1      0.114085   0.066640   1.712   0.0869 .
## chcond2      0.141158   0.083145   1.698   0.0896 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
```

```
##
## Null deviance: 5634.8 on 5189 degrees of freedom
## Residual deviance: 4379.5 on 5177 degrees of freedom
## AIC: 6737.1
##
## Number of Fisher Scoring iterations: 6
# This model fits the data because it improves the deviance.
```

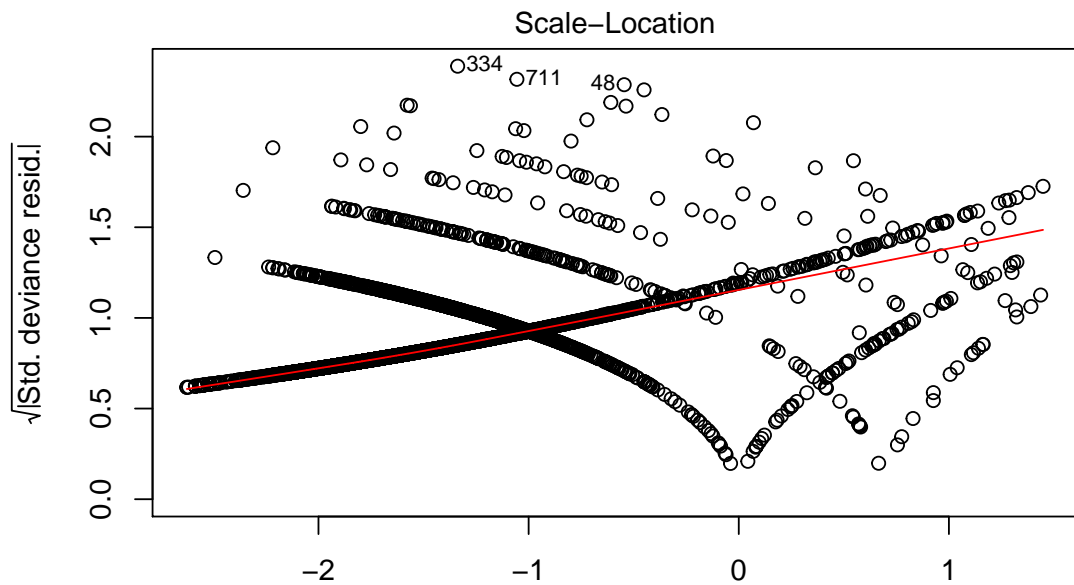
2. Plot the residuals and the fitted values-why are there lines of observations on the plot?

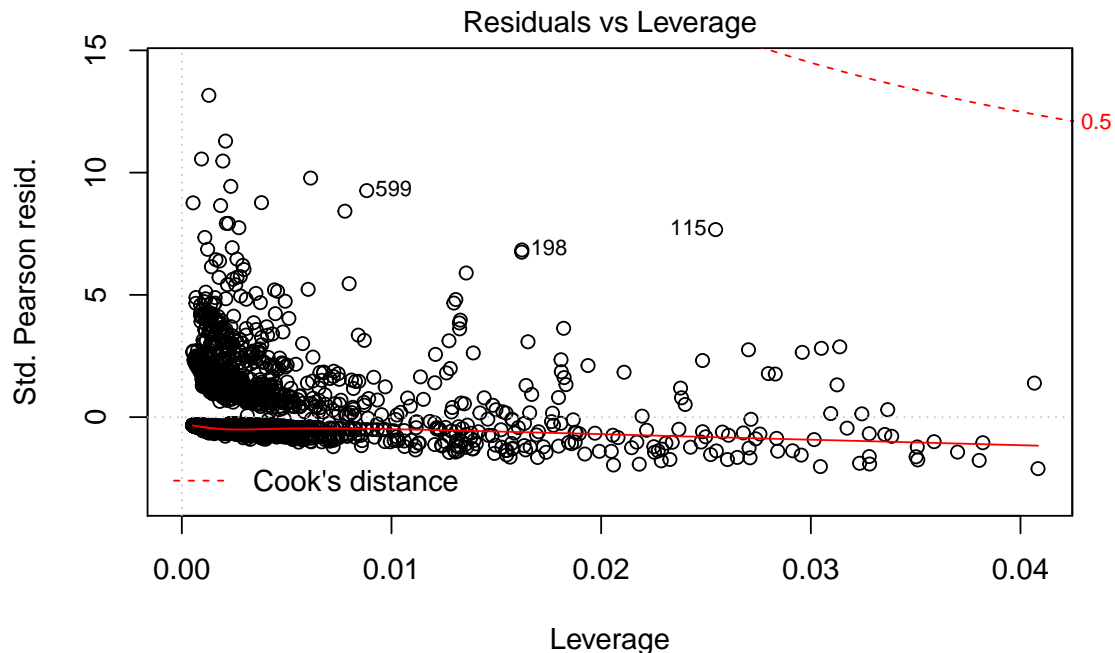
```
plot(mod_dvis)
```





Theoretical Quantiles
 glm(doctorco ~ sex + age + agesq + income + levyplus + freepoor + freerepa ...





`glm(doctorco ~ sex + age + agesq + income + levyplus + freepoor + freerepa ...`

3. What sort of person would be predicted to visit the doctor the most under your selected model?

According to the summary of my model, age is the most important predictor. Sex and illness are relative

4. For the last person in the dataset, compute the predicted probability distribution for their visits to the doctor, i.e., give the probability they visit 0,1,2, etc. times.

```
last<-dvisits[5190,]
pred<-predict(mod_dvis,last, type = "response")
probability<-matrix()
for (i in 0:10){
  probability[i] <- dpois(i, lambda = pred)
}
probability
```

```
## [1] 1.315726e-01 1.009055e-02 5.159087e-04 1.978300e-05 6.068779e-07
## [6] 1.551420e-08 3.399465e-10 6.517782e-12 1.110802e-13 1.703789e-15
```

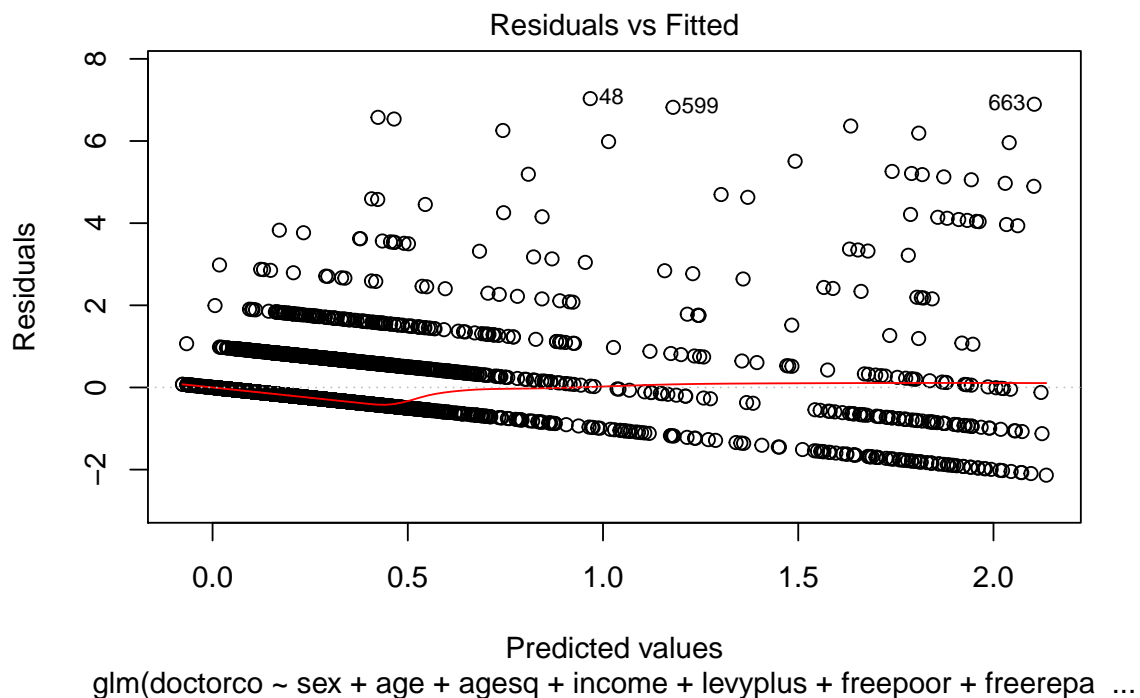
5. Fit a comparable (Gaussian) linear model and graphically compare the fits. Describe how they differ.

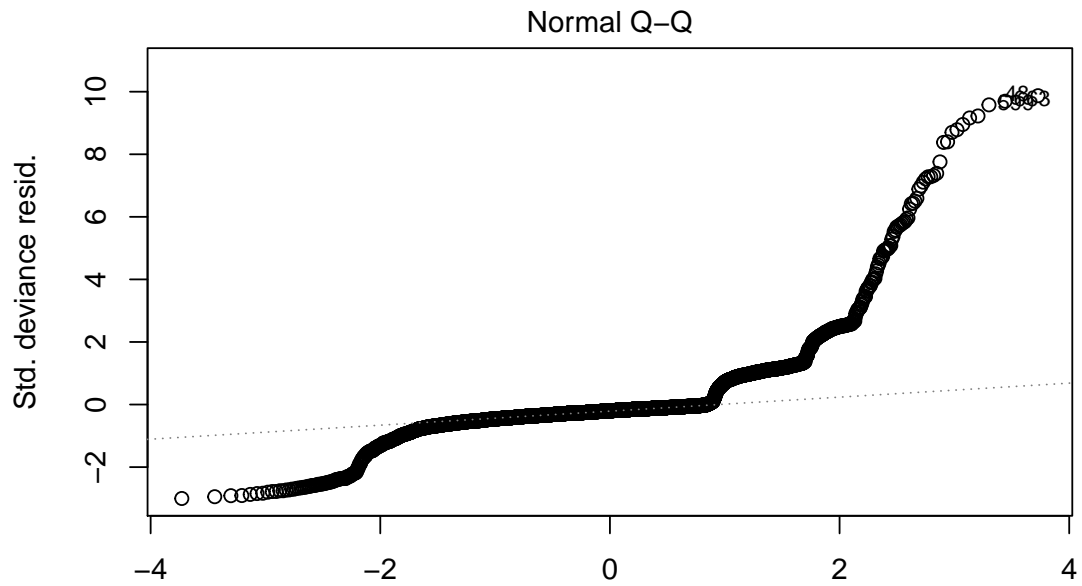
```
mod_dvis2<-glm(doctorco ~ sex + age + agesq + income + levyplus + freepoor + freerepa + illness + actdays + hscore + chcond1 + chcond2, family = gaussian, data = dvisits)
summary(mod_dvis2)
```

```
##
## Call:
## glm(formula = doctorco ~ sex + age + agesq + income + levyplus +
##     freepoor + freerepa + illness + actdays + hscore + chcond1 +
##     chcond2, family = gaussian, data = dvisits)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.1352  -0.2588  -0.1435  -0.0433   7.0327
##
## Coefficients:
```

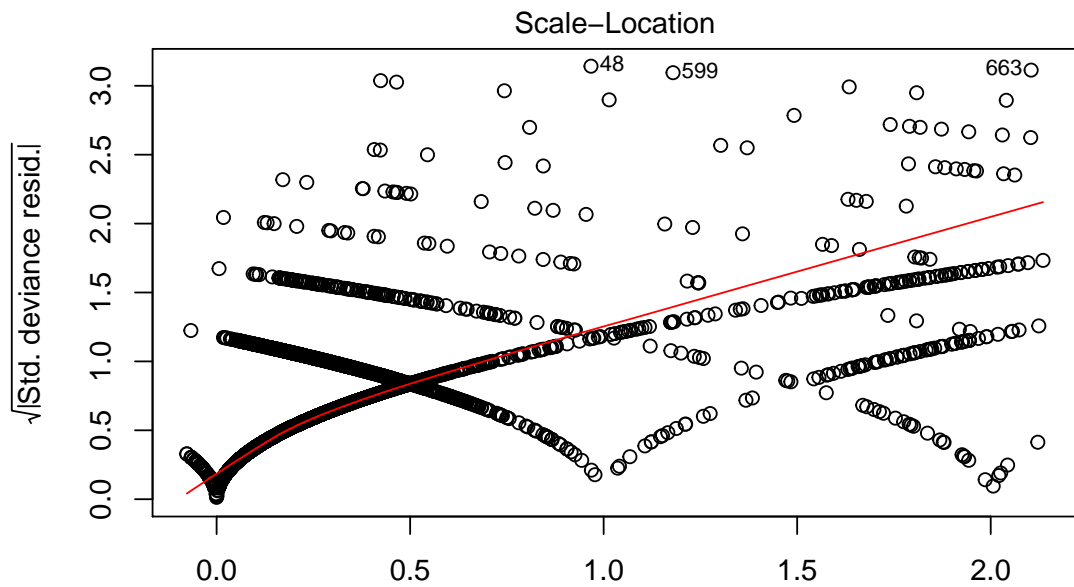
```
##           Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.027632   0.072220   0.383  0.70202
## sex         0.033811   0.021604   1.565  0.11764
## age         0.203201   0.410016   0.496  0.62020
## agesq      -0.062103   0.458716  -0.135  0.89231
## income     -0.057323   0.033089  -1.732  0.08326 .
## levyplus    0.035179   0.024882   1.414  0.15748
## freepoor   -0.103314   0.052471  -1.969  0.04901 *
## freerepa    0.033241   0.038157   0.871  0.38371
## illness     0.059946   0.008357   7.173 8.39e-13 ***
## actdays    0.103192   0.003657  28.216 < 2e-16 ***
## hscore      0.016976   0.005190   3.271  0.00108 **
## chcond1     0.004384   0.023740   0.185  0.85349
## chcond2     0.041617   0.035863   1.160  0.24592
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 0.5096272)
##
## Null deviance: 3305.5  on 5189  degrees of freedom
## Residual deviance: 2638.3  on 5177  degrees of freedom
## AIC: 11245
##
## Number of Fisher Scoring iterations: 2
```

```
plot(mod_dvis2)
```

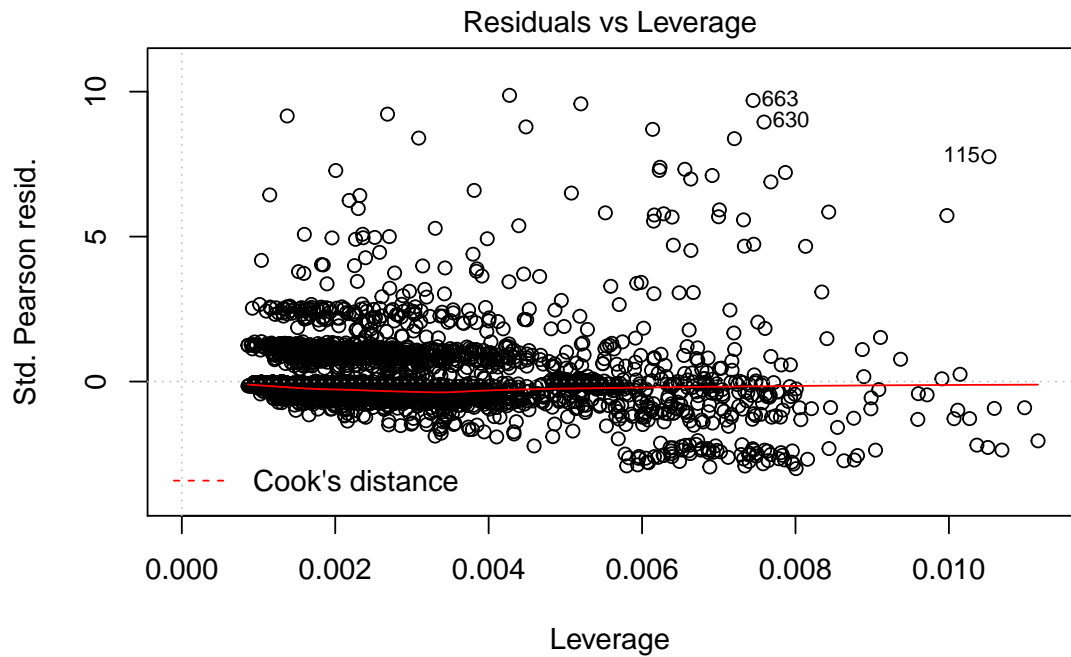




Theoretical Quantiles
 glm(doctorco ~ sex + age + agesq + income + levyplus + freepoor + freerepa ...



Predicted values
 glm(doctorco ~ sex + age + agesq + income + levyplus + freepoor + freerepa ...



glm(doctorco ~ sex + age + agesq + income + levyplus + freepoor + freerepa ...

Graphically, they don't have much differences.