Bayes Lab Day 4

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GLM with Bayes

With Bayesian analysis, generalized linear models are not that different from linear models. The main differences are the distribution of the dependent variables and the link functions used. Here, I will demonstrate how to estimate a Bayesian logit model. The first part of the model is, as always, loading and preparing the data.

Loading the data

The data are available in Stata (.dta) from the email I sent to the list of participants. These data are public opinion data about support for protectionist policies.

```
library(foreign)
library(R2jags)
```

```
## Loading required package: rjags

## Loading required package: coda

## Linked to JAGS 4.3.0

## Loaded modules: basemod,bugs

##
## Attaching package: 'R2jags'

## The following object is masked from 'package:coda':
##
##     traceplot
```

```
library(rjags)
library(lattice)
library(xtable)

#setting working director

setwd("/Users/sarahhunter/Documents")

dat<-read.dta("logit.hw.data.dta")
summary(dat)
```

```
##  protectionist        age            female          tumember
##  Min.   :0.0000   Min.   :18.00   Min.   :0.0000   Min.   :0.000
##  1st Qu.:0.0000   1st Qu.:36.00   1st Qu.:0.0000   1st Qu.:0.000
##  Median :1.0000   Median :46.00   Median :0.0000   Median :0.000
```

```
##  Mean   :0.5337   Mean   :48.83   Mean   :0.4345   Mean   :0.131
##  3rd Qu.:1.0000   3rd Qu.:62.00   3rd Qu.:1.0000   3rd Qu.:0.000
##  Max.   :1.0000   Max.   :92.00   Max.   :1.0000   Max.   :1.000
##     partyid         ideology        schooling
##  Min.   :0.000   Min.   :0.000   Min.   : 2.00
##  1st Qu.:1.000   1st Qu.:0.000   1st Qu.:12.00
##  Median :3.000   Median :0.000   Median :14.00
##  Mean   :2.913   Mean   :0.705   Mean   :13.89
##  3rd Qu.:5.000   3rd Qu.:2.000   3rd Qu.:16.00
##  Max.   :6.000   Max.   :2.000   Max.   :17.00
```

```
protectionist<-dat$protectionist
age<-dat$age
female<-dat$female
tumember<-dat$tumember
partyid<-dat$partyid
ideology<-dat$ideology
schooling<-dat$schooling
N<-length(dat$protectionist)

pro.data<-list("protectionist", "age", "female", "tumember", "partyid",
               "ideology", "schooling", "N")
pro.data<-list(protectionist=protectionist,age=age,
               female=female,tumember=tumember,partyid=partyid,
               ideology=ideology,schooling=schooling,
               N=length(protectionist))
```

Writing and Estimating the Model

When writing a GLM in JAGS, you need to first assign a distribution to the dependent variable. In the Bayesian linear model, you used the normal distribution. For at GLM, you need to think of the measurement metric (or typical values) of the dependent variable. Are you using a count? A dummy variable? An ordinal variable? Each of these will change how you parameterize the model. Some helpful distributions to think about are:

Probability Distribution	Call in JAGS	Parameters
Binomial Distribution	dbin	probability
Bernoulli Distribution	dbern	probability, integer size
Poisson Distribution	dpois	rate
Negative Binomial	dnbinom	probability, size

In my model, I use the Bernoulli distribution. The `p.bound` line of the code restrictions the probability to be between 0 and 1. Without that restriction, we could have out of bounds predicted probabilities.

```
logit.model.jags<-function(){
    for(i in 1:N){
        protectionist[i]~dbern(p.bound[i]);
        p.bound[i]<-max(0, min(1,p[i]))
        logit(p[i])<- mu[i] #link function
        mu[i]<-beta1
               +beta2*age[i]
               +beta3*female[i]
               +beta4*tumember[i]
```

```
                +beta5*partyid[i]
                +beta6*ideology[i]
                +beta7*schooling[i]

        #Log likelihood for each observation
                llh[i]<-protectionist[i]*log(p[i])+ (1-protectionist[i])*log(1-p[i])
    }
  #total log likelihood for the model
    sumllh<-sum(llh[])

    beta1~dnorm(0.0,0.1)
    beta2~dnorm(0.0,0.1)
    beta3~dnorm(0.0,0.1)
    beta4~dnorm(0.0,0.1)
    beta5~dnorm(0.0,0.1)
    beta6~dnorm(0.0,0.1)
    beta7~dnorm(0.0,0.1)
}

#Parameters to monitor
pro.params<-c("beta1", "beta2", "beta3", "beta4", "beta5", "beta6", "beta7", "p")

#estimating the model
pro.fit<-jags(data=pro.data, inits=NULL, pro.params, n.chains=2, n.iter=5000,
              n.burnin=500, model.file=logit.model.jags)
```

```
## module glm loaded
```

```
## Compiling model graph
##    Resolving undeclared variables
##    Allocating nodes
## Graph information:
##    Observed stochastic nodes: 817
##    Unobserved stochastic nodes: 7
##    Total graph size: 13647
##
## Initializing model
```

```
print(pro.fit)
```

```
## Inference for Bugs model at "/var/folders/dx/pkx9cyj1089843ljm_jzj3pm0000gn/T//RtmpGm3cAX/model3fc52
##  2 chains, each with 5000 iterations (first 500 discarded), n.thin = 4
##  n.sims = 2250 iterations saved
##            mu.vect sd.vect    2.5%     25%     50%     75%   97.5%  Rhat
## beta1        3.420   0.543   2.335   3.057   3.403   3.788   4.487 1.044
## beta2        0.006   0.004  -0.002   0.003   0.006   0.009   0.015 1.013
## beta3        0.628   0.161   0.307   0.518   0.630   0.732   0.947 1.003
## beta4        0.217   0.231  -0.225   0.060   0.211   0.377   0.673 1.003
## beta5       -0.094   0.042  -0.176  -0.121  -0.093  -0.066  -0.011 1.003
## beta6       -0.277   0.096  -0.471  -0.343  -0.276  -0.213  -0.092 1.003
## beta7       -0.244   0.031  -0.304  -0.266  -0.244  -0.224  -0.180 1.020
## p[1]         0.397   0.036   0.326   0.372   0.397   0.421   0.468 1.003
## p[2]         0.485   0.060   0.371   0.444   0.484   0.526   0.602 1.002
## p[3]         0.801   0.036   0.721   0.777   0.803   0.826   0.867 1.003
## p[4]         0.776   0.029   0.717   0.758   0.778   0.796   0.826 1.006
```

```
## p[5]         0.429   0.038    0.359    0.403    0.428    0.453    0.504 1.003
## p[6]         0.684   0.039    0.605    0.658    0.685    0.711    0.759 1.001
## p[7]         0.703   0.038    0.625    0.678    0.704    0.730    0.773 1.003
## p[8]         0.319   0.040    0.247    0.292    0.318    0.345    0.401 1.003
## p[9]         0.724   0.047    0.628    0.692    0.726    0.757    0.810 1.002
## p[10]        0.455   0.042    0.371    0.426    0.456    0.484    0.536 1.003
## p[11]        0.561   0.045    0.471    0.531    0.561    0.590    0.644 1.004
## p[12]        0.564   0.037    0.492    0.539    0.563    0.590    0.637 1.006
## p[13]        0.816   0.047    0.716    0.786    0.821    0.850    0.897 1.004
## p[14]        0.701   0.049    0.601    0.670    0.702    0.734    0.793 1.005
## p[15]        0.826   0.033    0.757    0.805    0.829    0.848    0.885 1.001
## p[16]        0.443   0.045    0.357    0.413    0.444    0.474    0.528 1.001
## p[17]        0.393   0.044    0.309    0.363    0.394    0.424    0.478 1.002
## p[18]        0.629   0.047    0.533    0.598    0.630    0.661    0.720 1.001
## p[19]        0.666   0.051    0.564    0.632    0.669    0.703    0.760 1.010
## p[20]        0.480   0.035    0.411    0.456    0.480    0.504    0.548 1.006
## p[21]        0.269   0.033    0.210    0.246    0.268    0.291    0.339 1.008
## p[22]        0.585   0.035    0.519    0.561    0.585    0.610    0.653 1.009
## p[23]        0.445   0.045    0.352    0.415    0.444    0.476    0.533 1.006
## p[24]        0.838   0.042    0.747    0.813    0.841    0.867    0.908 1.001
## p[25]        0.221   0.032    0.164    0.197    0.219    0.241    0.290 1.003
## p[26]        0.317   0.053    0.223    0.281    0.313    0.350    0.426 1.001
## p[27]        0.549   0.044    0.466    0.519    0.551    0.580    0.633 1.001
## p[28]        0.606   0.052    0.503    0.570    0.607    0.643    0.700 1.006
## p[29]        0.624   0.046    0.534    0.593    0.625    0.656    0.710 1.004
## p[30]        0.462   0.045    0.375    0.431    0.462    0.493    0.553 1.005
## p[31]        0.662   0.059    0.538    0.622    0.665    0.703    0.769 1.016
## p[32]        0.610   0.055    0.500    0.574    0.614    0.648    0.713 1.011
## p[33]        0.450   0.042    0.367    0.422    0.452    0.479    0.531 1.002
## p[34]        0.391   0.053    0.289    0.355    0.391    0.426    0.498 1.006
## p[35]        0.462   0.042    0.379    0.433    0.464    0.492    0.546 1.004
## p[36]        0.383   0.034    0.318    0.359    0.382    0.405    0.455 1.011
## p[37]        0.304   0.037    0.239    0.278    0.303    0.327    0.380 1.006
## p[38]        0.486   0.044    0.403    0.456    0.487    0.516    0.576 1.005
## p[39]        0.714   0.035    0.643    0.690    0.715    0.739    0.778 1.009
## p[40]        0.749   0.029    0.689    0.730    0.750    0.769    0.801 1.002
## p[41]        0.323   0.042    0.246    0.294    0.321    0.350    0.413 1.005
## p[42]        0.563   0.048    0.468    0.531    0.564    0.597    0.656 1.001
## p[43]        0.684   0.038    0.605    0.659    0.685    0.709    0.754 1.002
## p[44]        0.549   0.045    0.461    0.519    0.548    0.579    0.637 1.007
## p[45]        0.603   0.054    0.496    0.567    0.605    0.641    0.706 1.003
## p[46]        0.736   0.030    0.673    0.717    0.737    0.757    0.791 1.006
## p[47]        0.310   0.039    0.239    0.284    0.308    0.336    0.386 1.001
## p[48]        0.648   0.043    0.562    0.620    0.649    0.676    0.729 1.011
## p[49]        0.459   0.033    0.398    0.435    0.459    0.482    0.526 1.003
## p[50]        0.497   0.042    0.417    0.468    0.497    0.526    0.577 1.008
## p[51]        0.467   0.068    0.335    0.421    0.465    0.513    0.600 1.001
## p[52]        0.621   0.060    0.506    0.581    0.622    0.663    0.734 1.003
## p[53]        0.382   0.046    0.294    0.350    0.382    0.413    0.472 1.001
## p[54]        0.479   0.046    0.390    0.447    0.479    0.510    0.571 1.008
## p[55]        0.308   0.047    0.221    0.276    0.305    0.339    0.407 1.008
## p[56]        0.478   0.058    0.368    0.438    0.477    0.516    0.597 1.004
## p[57]        0.833   0.034    0.759    0.812    0.836    0.858    0.893 1.028
## p[58]        0.313   0.035    0.249    0.289    0.312    0.336    0.386 1.005
```

```
## p[59]        0.881   0.033    0.809    0.862    0.885    0.904    0.936 1.008
## p[60]        0.501   0.050    0.402    0.467    0.502    0.535    0.595 1.008
## p[61]        0.765   0.032    0.701    0.744    0.767    0.788    0.823 1.001
## p[62]        0.778   0.043    0.688    0.750    0.781    0.809    0.853 1.031
## p[63]        0.663   0.032    0.598    0.641    0.664    0.685    0.721 1.001
## p[64]        0.645   0.054    0.536    0.609    0.647    0.683    0.745 1.003
## p[65]        0.729   0.040    0.643    0.702    0.730    0.757    0.803 1.003
## p[66]        0.593   0.033    0.530    0.569    0.593    0.616    0.655 1.007
## p[67]        0.783   0.032    0.716    0.762    0.785    0.805    0.839 1.002
## p[68]        0.419   0.065    0.297    0.374    0.416    0.462    0.548 1.001
## p[69]        0.741   0.033    0.674    0.719    0.741    0.764    0.801 1.014
## p[70]        0.781   0.034    0.708    0.758    0.783    0.805    0.842 1.005
## p[71]        0.457   0.068    0.325    0.411    0.454    0.502    0.591 1.001
## p[72]        0.904   0.026    0.846    0.889    0.908    0.923    0.945 1.012
## p[73]        0.841   0.036    0.763    0.819    0.843    0.866    0.903 1.001
## p[74]        0.385   0.046    0.298    0.353    0.385    0.416    0.474 1.001
## p[75]        0.671   0.037    0.596    0.647    0.673    0.697    0.742 1.005
## p[76]        0.316   0.033    0.253    0.292    0.314    0.338    0.383 1.004
## p[77]        0.396   0.065    0.273    0.351    0.393    0.439    0.529 1.001
## p[78]        0.634   0.031    0.573    0.613    0.634    0.655    0.692 1.002
## p[79]        0.703   0.054    0.589    0.668    0.705    0.740    0.798 1.005
## p[80]        0.845   0.040    0.756    0.821    0.848    0.873    0.911 1.006
## p[81]        0.323   0.038    0.252    0.297    0.323    0.347    0.403 1.011
## p[82]        0.236   0.036    0.172    0.212    0.234    0.259    0.312 1.004
## p[83]        0.356   0.034    0.291    0.334    0.356    0.378    0.428 1.006
## p[84]        0.469   0.043    0.384    0.440    0.470    0.499    0.552 1.001
## p[85]        0.382   0.056    0.279    0.345    0.379    0.419    0.493 1.001
## p[86]        0.458   0.044    0.372    0.428    0.459    0.488    0.544 1.001
## p[87]        0.384   0.040    0.310    0.356    0.384    0.411    0.463 1.005
## p[88]        0.299   0.035    0.234    0.273    0.297    0.322    0.370 1.001
## p[89]        0.697   0.049    0.596    0.665    0.699    0.732    0.785 1.009
## p[90]        0.512   0.071    0.374    0.463    0.509    0.561    0.655 1.001
## p[91]        0.747   0.031    0.683    0.727    0.748    0.768    0.803 1.011
## p[92]        0.279   0.031    0.224    0.257    0.278    0.300    0.343 1.005
## p[93]        0.759   0.052    0.650    0.726    0.762    0.796    0.848 1.005
## p[94]        0.585   0.044    0.499    0.555    0.586    0.615    0.667 1.003
## p[95]        0.729   0.040    0.643    0.702    0.730    0.757    0.803 1.003
## p[96]        0.840   0.026    0.787    0.824    0.841    0.858    0.886 1.002
## p[97]        0.718   0.041    0.637    0.690    0.719    0.746    0.796 1.003
## p[98]        0.587   0.035    0.520    0.564    0.586    0.610    0.654 1.001
## p[99]        0.522   0.041    0.444    0.495    0.521    0.550    0.601 1.001
## p[100]       0.522   0.056    0.414    0.483    0.521    0.562    0.629 1.005
## p[101]       0.315   0.050    0.224    0.279    0.312    0.347    0.416 1.018
## p[102]       0.658   0.046    0.563    0.627    0.660    0.689    0.743 1.006
## p[103]       0.275   0.039    0.204    0.247    0.273    0.299    0.358 1.007
## p[104]       0.344   0.056    0.242    0.306    0.341    0.379    0.458 1.001
## p[105]       0.304   0.034    0.241    0.279    0.302    0.327    0.374 1.002
## p[106]       0.293   0.039    0.220    0.266    0.292    0.319    0.375 1.015
## p[107]       0.236   0.038    0.168    0.210    0.234    0.259    0.319 1.016
## p[108]       0.300   0.035    0.236    0.275    0.299    0.324    0.371 1.002
## p[109]       0.361   0.040    0.286    0.333    0.360    0.387    0.442 1.003
## p[110]       0.422   0.037    0.352    0.397    0.421    0.447    0.497 1.001
## p[111]       0.459   0.046    0.371    0.427    0.459    0.489    0.552 1.003
## p[112]       0.857   0.028    0.796    0.840    0.859    0.876    0.907 1.002
```

```
## p[113]       0.713   0.043    0.623    0.684    0.715    0.743    0.792 1.001
## p[114]       0.398   0.065    0.276    0.351    0.399    0.441    0.530 1.001
## p[115]       0.422   0.037    0.352    0.397    0.421    0.447    0.497 1.001
## p[116]       0.477   0.060    0.361    0.435    0.476    0.519    0.594 1.003
## p[117]       0.775   0.035    0.703    0.751    0.776    0.799    0.843 1.001
## p[118]       0.344   0.056    0.243    0.305    0.341    0.379    0.459 1.001
## p[119]       0.245   0.035    0.182    0.221    0.244    0.268    0.316 1.001
## p[120]       0.448   0.046    0.359    0.418    0.447    0.479    0.537 1.001
## p[121]       0.467   0.051    0.368    0.433    0.466    0.501    0.564 1.001
## p[122]       0.410   0.045    0.323    0.380    0.410    0.440    0.500 1.001
## p[123]       0.698   0.039    0.619    0.673    0.698    0.726    0.771 1.009
## p[124]       0.686   0.039    0.607    0.660    0.688    0.713    0.758 1.007
## p[125]       0.705   0.052    0.599    0.671    0.707    0.741    0.800 1.002
## p[126]       0.666   0.038    0.587    0.641    0.667    0.692    0.735 1.006
## p[127]       0.554   0.041    0.471    0.527    0.556    0.582    0.633 1.002
## p[128]       0.473   0.071    0.338    0.424    0.470    0.523    0.617 1.001
## p[129]       0.549   0.045    0.460    0.520    0.548    0.580    0.639 1.006
## p[130]       0.443   0.047    0.352    0.412    0.443    0.475    0.534 1.001
## p[131]       0.654   0.046    0.561    0.625    0.655    0.686    0.741 1.002
## p[132]       0.834   0.027    0.778    0.817    0.836    0.853    0.881 1.007
## p[133]       0.931   0.022    0.880    0.919    0.934    0.947    0.965 1.008
## p[134]       0.849   0.028    0.788    0.832    0.852    0.869    0.899 1.005
## p[135]       0.693   0.037    0.617    0.668    0.694    0.718    0.762 1.005
## p[136]       0.300   0.035    0.236    0.275    0.299    0.324    0.371 1.002
## p[137]       0.635   0.040    0.556    0.610    0.635    0.662    0.713 1.001
## p[138]       0.631   0.037    0.557    0.606    0.632    0.657    0.700 1.002
## p[139]       0.897   0.025    0.842    0.881    0.900    0.915    0.939 1.001
## p[140]       0.695   0.035    0.625    0.672    0.695    0.720    0.763 1.001
## p[141]       0.570   0.042    0.486    0.542    0.570    0.598    0.649 1.002
## p[142]       0.779   0.031    0.715    0.759    0.780    0.800    0.837 1.001
## p[143]       0.385   0.059    0.275    0.343    0.383    0.423    0.503 1.001
## p[144]       0.461   0.053    0.359    0.424    0.461    0.497    0.567 1.001
## p[145]       0.287   0.036    0.223    0.262    0.286    0.311    0.364 1.002
## p[146]       0.445   0.047    0.354    0.414    0.444    0.477    0.535 1.001
## p[147]       0.618   0.042    0.537    0.589    0.618    0.648    0.699 1.015
## p[148]       0.381   0.062    0.264    0.339    0.378    0.422    0.507 1.002
## p[149]       0.777   0.033    0.708    0.755    0.778    0.800    0.837 1.017
## p[150]       0.876   0.025    0.821    0.860    0.878    0.893    0.919 1.010
## p[151]       0.703   0.042    0.614    0.676    0.705    0.732    0.780 1.002
## p[152]       0.595   0.038    0.518    0.569    0.596    0.621    0.669 1.001
## p[153]       0.737   0.036    0.663    0.712    0.739    0.762    0.803 1.007
## p[154]       0.568   0.067    0.434    0.523    0.570    0.615    0.694 1.003
## p[155]       0.587   0.058    0.471    0.548    0.589    0.626    0.697 1.005
## p[156]       0.687   0.041    0.602    0.660    0.687    0.716    0.763 1.004
## p[157]       0.329   0.035    0.263    0.304    0.327    0.352    0.401 1.008
## p[158]       0.366   0.041    0.286    0.337    0.364    0.393    0.449 1.009
## p[159]       0.480   0.035    0.411    0.456    0.480    0.504    0.548 1.006
## p[160]       0.448   0.044    0.362    0.418    0.449    0.477    0.530 1.001
## p[161]       0.727   0.046    0.631    0.698    0.730    0.759    0.813 1.001
## p[162]       0.519   0.057    0.405    0.481    0.520    0.558    0.630 1.011
## p[163]       0.547   0.044    0.460    0.518    0.546    0.577    0.634 1.007
## p[164]       0.821   0.030    0.757    0.802    0.823    0.843    0.871 1.002
## p[165]       0.593   0.041    0.513    0.566    0.594    0.621    0.672 1.001
## p[166]       0.666   0.038    0.587    0.641    0.667    0.693    0.739 1.006
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## p[167]       0.587   0.056    0.475    0.549    0.587    0.627    0.693 1.002
## p[168]       0.562   0.040    0.482    0.535    0.561    0.590    0.643 1.001
## p[169]       0.438   0.063    0.314    0.396    0.438    0.479    0.566 1.008
## p[170]       0.375   0.041    0.298    0.347    0.375    0.403    0.460 1.014
## p[171]       0.879   0.025    0.827    0.864    0.881    0.897    0.922 1.002
## p[172]       0.609   0.039    0.533    0.583    0.609    0.636    0.681 1.002
## p[173]       0.275   0.039    0.204    0.247    0.273    0.299    0.358 1.007
## p[174]       0.624   0.036    0.551    0.600    0.625    0.649    0.691 1.001
## p[175]       0.841   0.027    0.785    0.824    0.843    0.860    0.888 1.003
## p[176]       0.559   0.045    0.469    0.529    0.560    0.589    0.643 1.004
## p[177]       0.664   0.056    0.547    0.627    0.665    0.703    0.770 1.001
## p[178]       0.259   0.036    0.195    0.233    0.257    0.282    0.338 1.009
## p[179]       0.310   0.032    0.252    0.288    0.309    0.330    0.376 1.008
## p[180]       0.538   0.043    0.454    0.509    0.537    0.567    0.624 1.004
## p[181]       0.510   0.048    0.416    0.479    0.511    0.543    0.605 1.007
## p[182]       0.901   0.022    0.850    0.888    0.904    0.917    0.938 1.013
## p[183]       0.792   0.039    0.710    0.767    0.795    0.820    0.861 1.002
## p[184]       0.424   0.047    0.333    0.392    0.424    0.457    0.518 1.007
## p[185]       0.672   0.042    0.587    0.644    0.673    0.701    0.750 1.003
## p[186]       0.263   0.032    0.205    0.241    0.262    0.285    0.332 1.005
## p[187]       0.664   0.050    0.563    0.631    0.664    0.700    0.757 1.009
## p[188]       0.431   0.058    0.325    0.390    0.429    0.470    0.550 1.001
## p[189]       0.507   0.061    0.387    0.466    0.509    0.548    0.621 1.006
## p[190]       0.543   0.036    0.476    0.518    0.542    0.568    0.613 1.008
## p[191]       0.294   0.036    0.231    0.269    0.293    0.316    0.369 1.003
## p[192]       0.597   0.038    0.521    0.571    0.597    0.623    0.670 1.001
## p[193]       0.452   0.030    0.393    0.432    0.452    0.472    0.512 1.001
## p[194]       0.663   0.035    0.592    0.640    0.664    0.687    0.730 1.003
## p[195]       0.416   0.068    0.287    0.367    0.414    0.461    0.551 1.005
## p[196]       0.799   0.042    0.706    0.772    0.803    0.828    0.873 1.008
## p[197]       0.782   0.033    0.711    0.760    0.783    0.805    0.843 1.004
## p[198]       0.579   0.037    0.507    0.553    0.578    0.606    0.650 1.011
## p[199]       0.655   0.040    0.573    0.628    0.656    0.682    0.731 1.009
## p[200]       0.570   0.042    0.486    0.542    0.570    0.598    0.649 1.002
## p[201]       0.635   0.042    0.549    0.605    0.635    0.664    0.713 1.001
## p[202]       0.502   0.071    0.367    0.453    0.502    0.549    0.640 1.001
## p[203]       0.300   0.030    0.246    0.279    0.299    0.320    0.362 1.001
## p[204]       0.633   0.064    0.504    0.591    0.635    0.676    0.752 1.001
## p[205]       0.540   0.037    0.468    0.515    0.540    0.566    0.613 1.001
## p[206]       0.646   0.061    0.523    0.605    0.647    0.687    0.759 1.002
## p[207]       0.314   0.033    0.252    0.290    0.313    0.337    0.381 1.004
## p[208]       0.317   0.033    0.254    0.293    0.316    0.339    0.385 1.004
## p[209]       0.324   0.034    0.260    0.300    0.323    0.346    0.394 1.006
## p[210]       0.725   0.040    0.642    0.699    0.727    0.753    0.798 1.003
## p[211]       0.827   0.031    0.761    0.807    0.830    0.850    0.882 1.009
## p[212]       0.606   0.066    0.468    0.561    0.608    0.651    0.732 1.007
## p[213]       0.385   0.047    0.293    0.353    0.383    0.417    0.480 1.007
## p[214]       0.309   0.031    0.250    0.287    0.307    0.329    0.374 1.008
## p[215]       0.673   0.036    0.602    0.649    0.674    0.697    0.741 1.001
## p[216]       0.692   0.051    0.583    0.658    0.695    0.727    0.788 1.002
## p[217]       0.647   0.049    0.546    0.614    0.648    0.681    0.741 1.001
## p[218]       0.524   0.059    0.406    0.484    0.525    0.564    0.638 1.011
## p[219]       0.325   0.032    0.269    0.303    0.324    0.346    0.389 1.003
## p[220]       0.892   0.023    0.841    0.878    0.894    0.909    0.930 1.006
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## p[221]       0.762   0.041    0.677    0.735    0.764    0.791    0.833 1.018
## p[222]       0.607   0.036    0.534    0.583    0.607    0.631    0.676 1.001
## p[223]       0.411   0.038    0.336    0.386    0.411    0.437    0.486 1.006
## p[224]       0.293   0.052    0.201    0.258    0.289    0.326    0.403 1.001
## p[225]       0.503   0.046    0.414    0.471    0.503    0.533    0.592 1.002
## p[226]       0.676   0.039    0.599    0.650    0.677    0.703    0.753 1.002
## p[227]       0.299   0.036    0.232    0.273    0.299    0.323    0.373 1.013
## p[228]       0.618   0.059    0.503    0.579    0.619    0.659    0.730 1.003
## p[229]       0.433   0.048    0.342    0.401    0.434    0.466    0.536 1.009
## p[230]       0.371   0.051    0.272    0.336    0.369    0.404    0.472 1.013
## p[231]       0.385   0.032    0.328    0.362    0.384    0.406    0.449 1.002
## p[232]       0.309   0.034    0.247    0.285    0.307    0.332    0.378 1.003
## p[233]       0.388   0.039    0.314    0.361    0.388    0.414    0.466 1.001
## p[234]       0.481   0.043    0.397    0.451    0.483    0.511    0.566 1.003
## p[235]       0.330   0.035    0.265    0.306    0.329    0.354    0.403 1.008
## p[236]       0.775   0.035    0.702    0.753    0.778    0.800    0.837 1.014
## p[237]       0.304   0.037    0.239    0.278    0.303    0.327    0.380 1.006
## p[238]       0.438   0.039    0.363    0.412    0.439    0.465    0.515 1.002
## p[239]       0.588   0.048    0.493    0.557    0.587    0.620    0.684 1.008
## p[240]       0.701   0.041    0.618    0.674    0.703    0.729    0.778 1.001
## p[241]       0.327   0.036    0.262    0.303    0.325    0.351    0.404 1.013
## p[242]       0.307   0.031    0.248    0.286    0.306    0.328    0.372 1.007
## p[243]       0.407   0.044    0.324    0.377    0.406    0.435    0.492 1.003
## p[244]       0.780   0.042    0.691    0.752    0.782    0.810    0.853 1.001
## p[245]       0.671   0.041    0.586    0.643    0.672    0.699    0.749 1.003
## p[246]       0.742   0.050    0.637    0.710    0.745    0.777    0.831 1.006
## p[247]       0.683   0.039    0.604    0.658    0.684    0.710    0.758 1.001
## p[248]       0.708   0.035    0.639    0.685    0.709    0.733    0.774 1.002
## p[249]       0.568   0.041    0.484    0.540    0.569    0.596    0.646 1.002
## p[250]       0.261   0.032    0.202    0.238    0.260    0.282    0.329 1.005
## p[251]       0.646   0.037    0.572    0.622    0.647    0.671    0.714 1.002
## p[252]       0.689   0.035    0.618    0.666    0.689    0.713    0.756 1.001
## p[253]       0.487   0.039    0.413    0.461    0.485    0.512    0.565 1.001
## p[254]       0.386   0.041    0.310    0.358    0.384    0.414    0.469 1.002
## p[255]       0.515   0.037    0.444    0.489    0.514    0.541    0.587 1.008
## p[256]       0.663   0.055    0.549    0.627    0.665    0.701    0.760 1.011
## p[257]       0.311   0.037    0.242    0.285    0.310    0.335    0.390 1.015
## p[258]       0.646   0.044    0.562    0.617    0.647    0.677    0.727 1.008
## p[259]       0.838   0.033    0.770    0.818    0.841    0.862    0.895 1.024
## p[260]       0.523   0.046    0.432    0.491    0.523    0.554    0.611 1.008
## p[261]       0.243   0.036    0.177    0.218    0.241    0.266    0.321 1.006
## p[262]       0.527   0.059    0.412    0.487    0.526    0.567    0.644 1.012
## p[263]       0.291   0.038    0.219    0.264    0.289    0.315    0.370 1.015
## p[264]       0.535   0.031    0.477    0.512    0.534    0.556    0.595 1.003
## p[265]       0.668   0.040    0.587    0.641    0.669    0.696    0.743 1.013
## p[266]       0.683   0.034    0.612    0.660    0.685    0.706    0.747 1.010
## p[267]       0.720   0.035    0.650    0.698    0.722    0.744    0.784 1.002
## p[268]       0.586   0.042    0.503    0.558    0.586    0.615    0.668 1.004
## p[269]       0.658   0.046    0.565    0.626    0.659    0.691    0.747 1.007
## p[270]       0.679   0.044    0.591    0.650    0.679    0.710    0.761 1.006
## p[271]       0.693   0.039    0.613    0.667    0.695    0.719    0.766 1.001
## p[272]       0.608   0.031    0.547    0.586    0.608    0.630    0.668 1.002
## p[273]       0.581   0.059    0.466    0.541    0.583    0.621    0.691 1.006
## p[274]       0.666   0.043    0.579    0.637    0.668    0.695    0.749 1.001
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## p[275]      0.852  0.028   0.793   0.835   0.854   0.872   0.899 1.023
## p[276]      0.837  0.035   0.763   0.816   0.839   0.861   0.898 1.001
## p[277]      0.932  0.021   0.882   0.920   0.935   0.947   0.963 1.002
## p[278]      0.819  0.030   0.756   0.800   0.822   0.841   0.870 1.003
## p[279]      0.890  0.025   0.837   0.874   0.892   0.908   0.933 1.001
## p[280]      0.808  0.043   0.717   0.781   0.811   0.839   0.881 1.004
## p[281]      0.432  0.040   0.357   0.405   0.432   0.459   0.513 1.011
## p[282]      0.422  0.042   0.342   0.393   0.423   0.450   0.504 1.001
## p[283]      0.361  0.035   0.294   0.336   0.360   0.385   0.433 1.011
## p[284]      0.278  0.038   0.210   0.251   0.276   0.302   0.358 1.001
## p[285]      0.431  0.043   0.350   0.402   0.432   0.460   0.516 1.001
## p[286]      0.637  0.037   0.566   0.612   0.636   0.663   0.708 1.005
## p[287]      0.419  0.038   0.347   0.393   0.418   0.445   0.494 1.003
## p[288]      0.555  0.047   0.461   0.522   0.556   0.586   0.642 1.005
## p[289]      0.605  0.053   0.500   0.569   0.606   0.640   0.703 1.001
## p[290]      0.438  0.043   0.355   0.408   0.438   0.468   0.522 1.005
## p[291]      0.300  0.036   0.236   0.274   0.299   0.323   0.375 1.004
## p[292]      0.216  0.033   0.158   0.193   0.213   0.236   0.287 1.002
## p[293]      0.673  0.037   0.599   0.648   0.674   0.698   0.743 1.004
## p[294]      0.526  0.041   0.445   0.498   0.525   0.553   0.607 1.002
## p[295]      0.759  0.033   0.690   0.738   0.761   0.783   0.818 1.015
## p[296]      0.361  0.030   0.305   0.340   0.361   0.381   0.423 1.006
## p[297]      0.557  0.037   0.484   0.532   0.557   0.583   0.629 1.001
## p[298]      0.293  0.032   0.234   0.271   0.291   0.314   0.361 1.005
## p[299]      0.274  0.050   0.186   0.241   0.271   0.306   0.378 1.001
## p[300]      0.622  0.049   0.524   0.590   0.622   0.655   0.717 1.006
## p[301]      0.724  0.040   0.641   0.697   0.726   0.754   0.799 1.010
## p[302]      0.845  0.031   0.779   0.826   0.848   0.867   0.899 1.018
## p[303]      0.310  0.055   0.209   0.271   0.307   0.345   0.424 1.003
## p[304]      0.506  0.050   0.409   0.472   0.505   0.539   0.606 1.009
## p[305]      0.580  0.040   0.503   0.554   0.580   0.607   0.657 1.011
## p[306]      0.685  0.041   0.599   0.658   0.685   0.714   0.761 1.005
## p[307]      0.543  0.042   0.461   0.515   0.541   0.571   0.626 1.003
## p[308]      0.339  0.040   0.264   0.311   0.337   0.364   0.425 1.015
## p[309]      0.341  0.031   0.285   0.319   0.341   0.362   0.406 1.006
## p[310]      0.433  0.044   0.352   0.403   0.432   0.463   0.521 1.005
## p[311]      0.766  0.035   0.690   0.743   0.768   0.791   0.831 1.013
## p[312]      0.748  0.029   0.688   0.729   0.749   0.768   0.800 1.002
## p[313]      0.424  0.043   0.343   0.395   0.424   0.453   0.509 1.001
## p[314]      0.642  0.044   0.556   0.611   0.643   0.673   0.723 1.002
## p[315]      0.617  0.043   0.535   0.588   0.616   0.647   0.700 1.016
## p[316]      0.419  0.045   0.334   0.389   0.419   0.448   0.509 1.005
## p[317]      0.571  0.053   0.466   0.535   0.573   0.608   0.672 1.001
## p[318]      0.811  0.031   0.743   0.792   0.812   0.833   0.864 1.017
## p[319]      0.786  0.031   0.721   0.766   0.788   0.808   0.842 1.009
## p[320]      0.567  0.042   0.481   0.539   0.567   0.595   0.648 1.003
## p[321]      0.323  0.055   0.223   0.284   0.321   0.358   0.434 1.019
## p[322]      0.393  0.044   0.309   0.363   0.394   0.424   0.478 1.002
## p[323]      0.318  0.033   0.255   0.294   0.317   0.340   0.386 1.005
## p[324]      0.290  0.043   0.211   0.260   0.288   0.317   0.384 1.011
## p[325]      0.308  0.034   0.246   0.283   0.306   0.331   0.377 1.002
## p[326]      0.545  0.035   0.478   0.521   0.545   0.569   0.614 1.006
## p[327]      0.242  0.034   0.181   0.218   0.240   0.263   0.315 1.004
## p[328]      0.240  0.056   0.145   0.200   0.236   0.275   0.358 1.001
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## p[329]       0.750   0.036    0.677    0.727    0.752    0.776    0.815 1.002
## p[330]       0.750   0.036    0.677    0.727    0.752    0.776    0.815 1.002
## p[331]       0.704   0.029    0.644    0.686    0.705    0.724    0.758 1.003
## p[332]       0.250   0.051    0.162    0.213    0.246    0.282    0.357 1.003
## p[333]       0.392   0.035    0.328    0.368    0.391    0.417    0.464 1.003
## p[334]       0.574   0.057    0.461    0.535    0.574    0.614    0.682 1.009
## p[335]       0.258   0.036    0.194    0.232    0.256    0.280    0.336 1.009
## p[336]       0.500   0.044    0.416    0.469    0.498    0.531    0.587 1.011
## p[337]       0.850   0.030    0.785    0.830    0.851    0.872    0.905 1.001
## p[338]       0.272   0.039    0.203    0.245    0.271    0.297    0.356 1.006
## p[339]       0.287   0.037    0.219    0.261    0.286    0.311    0.363 1.014
## p[340]       0.633   0.049    0.533    0.600    0.634    0.667    0.723 1.005
## p[341]       0.867   0.030    0.799    0.849    0.870    0.889    0.916 1.004
## p[342]       0.506   0.064    0.379    0.463    0.503    0.549    0.629 1.001
## p[343]       0.347   0.065    0.225    0.302    0.344    0.390    0.479 1.002
## p[344]       0.705   0.060    0.574    0.666    0.709    0.747    0.815 1.015
## p[345]       0.751   0.048    0.649    0.720    0.754    0.785    0.837 1.004
## p[346]       0.457   0.034    0.395    0.433    0.457    0.481    0.527 1.004
## p[347]       0.612   0.034    0.547    0.589    0.612    0.636    0.678 1.010
## p[348]       0.397   0.057    0.292    0.358    0.395    0.435    0.513 1.002
## p[349]       0.771   0.037    0.694    0.746    0.773    0.797    0.836 1.016
## p[350]       0.313   0.033    0.251    0.289    0.312    0.336    0.380 1.003
## p[351]       0.568   0.041    0.488    0.541    0.568    0.596    0.648 1.002
## p[352]       0.510   0.052    0.412    0.475    0.510    0.546    0.616 1.007
## p[353]       0.614   0.054    0.505    0.577    0.614    0.651    0.719 1.007
## p[354]       0.307   0.037    0.240    0.280    0.306    0.330    0.384 1.006
## p[355]       0.358   0.040    0.282    0.331    0.357    0.384    0.438 1.005
## p[356]       0.305   0.031    0.246    0.283    0.303    0.325    0.370 1.007
## p[357]       0.688   0.047    0.590    0.657    0.690    0.720    0.777 1.006
## p[358]       0.497   0.038    0.423    0.472    0.496    0.523    0.575 1.002
## p[359]       0.298   0.031    0.241    0.277    0.297    0.319    0.364 1.005
## p[360]       0.367   0.056    0.265    0.328    0.365    0.402    0.484 1.018
## p[361]       0.480   0.043    0.395    0.450    0.481    0.510    0.565 1.002
## p[362]       0.691   0.035    0.621    0.668    0.692    0.716    0.759 1.001
## p[363]       0.415   0.046    0.327    0.384    0.415    0.447    0.507 1.005
## p[364]       0.344   0.043    0.265    0.314    0.343    0.372    0.434 1.016
## p[365]       0.602   0.054    0.495    0.565    0.604    0.639    0.704 1.003
## p[366]       0.316   0.056    0.212    0.279    0.312    0.350    0.434 1.001
## p[367]       0.915   0.023    0.861    0.900    0.917    0.931    0.952 1.012
## p[368]       0.824   0.035    0.746    0.801    0.826    0.849    0.886 1.001
## p[369]       0.410   0.040    0.335    0.383    0.410    0.436    0.490 1.001
## p[370]       0.461   0.043    0.379    0.432    0.461    0.490    0.545 1.001
## p[371]       0.399   0.041    0.322    0.371    0.398    0.426    0.482 1.014
## p[372]       0.297   0.032    0.235    0.274    0.296    0.318    0.366 1.011
## p[373]       0.691   0.041    0.609    0.664    0.692    0.718    0.769 1.003
## p[374]       0.626   0.053    0.521    0.589    0.627    0.661    0.728 1.004
## p[375]       0.480   0.049    0.385    0.446    0.480    0.514    0.575 1.001
## p[376]       0.451   0.041    0.372    0.423    0.449    0.479    0.531 1.001
## p[377]       0.668   0.039    0.589    0.642    0.668    0.695    0.740 1.004
## p[378]       0.747   0.046    0.646    0.717    0.750    0.781    0.829 1.005
## p[379]       0.294   0.037    0.226    0.268    0.292    0.319    0.367 1.001
## p[380]       0.648   0.043    0.562    0.620    0.649    0.676    0.729 1.011
## p[381]       0.401   0.037    0.329    0.375    0.401    0.426    0.477 1.006
## p[382]       0.337   0.031    0.282    0.315    0.336    0.358    0.400 1.005
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## p[383]       0.419   0.056    0.315    0.380    0.416    0.457    0.535 1.001
## p[384]       0.798   0.046    0.701    0.769    0.801    0.831    0.876 1.008
## p[385]       0.344   0.039    0.272    0.318    0.344    0.370    0.424 1.007
## p[386]       0.662   0.051    0.561    0.628    0.663    0.698    0.755 1.005
## p[387]       0.783   0.032    0.716    0.762    0.785    0.806    0.840 1.011
## p[388]       0.650   0.052    0.544    0.614    0.651    0.686    0.745 1.004
## p[389]       0.295   0.032    0.236    0.273    0.293    0.315    0.361 1.005
## p[390]       0.571   0.063    0.441    0.530    0.572    0.614    0.691 1.002
## p[391]       0.387   0.057    0.279    0.349    0.384    0.425    0.502 1.002
## p[392]       0.676   0.047    0.581    0.644    0.678    0.708    0.763 1.001
## p[393]       0.929   0.023    0.876    0.916    0.933    0.946    0.965 1.021
## p[394]       0.312   0.040    0.241    0.286    0.311    0.338    0.395 1.002
## p[395]       0.628   0.051    0.524    0.593    0.630    0.662    0.724 1.008
## p[396]       0.685   0.038    0.606    0.660    0.687    0.711    0.755 1.001
## p[397]       0.578   0.035    0.510    0.555    0.577    0.602    0.647 1.003
## p[398]       0.631   0.048    0.532    0.599    0.632    0.665    0.721 1.005
## p[399]       0.773   0.045    0.678    0.744    0.775    0.804    0.852 1.012
## p[400]       0.451   0.045    0.363    0.420    0.450    0.481    0.538 1.001
## p[401]       0.508   0.034    0.443    0.486    0.508    0.532    0.573 1.005
## p[402]       0.366   0.044    0.284    0.336    0.364    0.395    0.454 1.002
## p[403]       0.698   0.055    0.582    0.662    0.700    0.737    0.795 1.004
## p[404]       0.676   0.034    0.608    0.655    0.677    0.700    0.737 1.001
## p[405]       0.285   0.034    0.223    0.261    0.283    0.306    0.355 1.004
## p[406]       0.281   0.041    0.207    0.253    0.279    0.306    0.367 1.009
## p[407]       0.419   0.053    0.321    0.383    0.418    0.454    0.526 1.009
## p[408]       0.477   0.029    0.423    0.456    0.478    0.497    0.535 1.002
## p[409]       0.600   0.049    0.502    0.567    0.600    0.633    0.695 1.005
## p[410]       0.586   0.042    0.503    0.558    0.586    0.615    0.668 1.004
## p[411]       0.626   0.034    0.558    0.604    0.627    0.649    0.689 1.001
## p[412]       0.586   0.038    0.512    0.561    0.587    0.612    0.659 1.009
## p[413]       0.370   0.057    0.267    0.330    0.366    0.409    0.491 1.001
## p[414]       0.454   0.031    0.394    0.433    0.453    0.475    0.518 1.002
## p[415]       0.714   0.043    0.624    0.686    0.717    0.744    0.794 1.001
## p[416]       0.580   0.044    0.494    0.551    0.580    0.611    0.666 1.005
## p[417]       0.650   0.029    0.589    0.631    0.651    0.670    0.705 1.001
## p[418]       0.722   0.048    0.624    0.691    0.724    0.754    0.808 1.008
## p[419]       0.711   0.039    0.632    0.686    0.712    0.737    0.785 1.002
## p[420]       0.448   0.056    0.341    0.409    0.448    0.486    0.559 1.004
## p[421]       0.387   0.053    0.285    0.351    0.386    0.422    0.494 1.005
## p[422]       0.650   0.033    0.582    0.629    0.651    0.673    0.712 1.001
## p[423]       0.703   0.037    0.627    0.679    0.704    0.730    0.773 1.008
## p[424]       0.417   0.044    0.333    0.387    0.416    0.447    0.504 1.001
## p[425]       0.368   0.037    0.299    0.342    0.367    0.392    0.442 1.002
## p[426]       0.707   0.036    0.632    0.684    0.707    0.732    0.774 1.007
## p[427]       0.731   0.033    0.663    0.710    0.732    0.754    0.791 1.002
## p[428]       0.742   0.049    0.640    0.709    0.746    0.777    0.827 1.015
## p[429]       0.347   0.031    0.291    0.325    0.346    0.368    0.411 1.004
## p[430]       0.404   0.062    0.288    0.360    0.406    0.446    0.529 1.002
## p[431]       0.527   0.052    0.428    0.492    0.528    0.564    0.624 1.001
## p[432]       0.439   0.036    0.368    0.414    0.437    0.463    0.512 1.003
## p[433]       0.326   0.041    0.250    0.298    0.324    0.353    0.410 1.001
## p[434]       0.704   0.042    0.615    0.677    0.706    0.734    0.782 1.002
## p[435]       0.709   0.037    0.632    0.684    0.712    0.734    0.778 1.001
## p[436]       0.646   0.046    0.551    0.616    0.647    0.678    0.733 1.012
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## p[437]       0.299   0.035    0.234    0.273    0.297    0.322    0.370 1.001
## p[438]       0.336   0.054    0.236    0.299    0.332    0.372    0.445 1.005
## p[439]       0.261   0.032    0.202    0.238    0.260    0.282    0.329 1.005
## p[440]       0.869   0.030    0.802    0.850    0.872    0.890    0.918 1.002
## p[441]       0.361   0.043    0.279    0.332    0.359    0.389    0.449 1.013
## p[442]       0.316   0.034    0.253    0.292    0.315    0.339    0.386 1.002
## p[443]       0.448   0.032    0.387    0.426    0.447    0.470    0.512 1.001
## p[444]       0.525   0.056    0.415    0.486    0.525    0.563    0.632 1.006
## p[445]       0.568   0.060    0.449    0.528    0.568    0.609    0.682 1.003
## p[446]       0.255   0.033    0.195    0.232    0.254    0.277    0.322 1.003
## p[447]       0.608   0.035    0.541    0.583    0.607    0.633    0.675 1.012
## p[448]       0.638   0.036    0.570    0.614    0.637    0.663    0.708 1.001
## p[449]       0.584   0.063    0.458    0.541    0.586    0.626    0.704 1.007
## p[450]       0.868   0.035    0.792    0.846    0.872    0.893    0.927 1.012
## p[451]       0.482   0.043    0.396    0.453    0.483    0.510    0.567 1.004
## p[452]       0.842   0.027    0.784    0.824    0.845    0.861    0.888 1.001
## p[453]       0.589   0.045    0.500    0.559    0.590    0.620    0.673 1.004
## p[454]       0.752   0.035    0.679    0.728    0.753    0.777    0.819 1.001
## p[455]       0.602   0.045    0.513    0.571    0.602    0.632    0.687 1.004
## p[456]       0.796   0.035    0.720    0.773    0.799    0.821    0.858 1.011
## p[457]       0.451   0.043    0.365    0.421    0.452    0.480    0.532 1.001
## p[458]       0.248   0.034    0.188    0.224    0.247    0.270    0.323 1.006
## p[459]       0.543   0.041    0.466    0.516    0.543    0.572    0.624 1.003
## p[460]       0.663   0.038    0.587    0.637    0.664    0.689    0.732 1.011
## p[461]       0.764   0.030    0.702    0.744    0.765    0.784    0.818 1.001
## p[462]       0.492   0.047    0.400    0.460    0.492    0.524    0.584 1.005
## p[463]       0.744   0.034    0.676    0.721    0.746    0.767    0.804 1.013
## p[464]       0.481   0.056    0.373    0.442    0.480    0.519    0.592 1.014
## p[465]       0.275   0.034    0.212    0.250    0.274    0.297    0.345 1.004
## p[466]       0.377   0.032    0.316    0.354    0.376    0.398    0.444 1.009
## p[467]       0.314   0.038    0.242    0.288    0.313    0.339    0.395 1.016
## p[468]       0.672   0.036    0.601    0.648    0.673    0.696    0.741 1.001
## p[469]       0.270   0.039    0.201    0.243    0.268    0.294    0.353 1.006
## p[470]       0.353   0.043    0.273    0.323    0.351    0.381    0.440 1.014
## p[471]       0.483   0.043    0.398    0.454    0.484    0.512    0.569 1.004
## p[472]       0.685   0.042    0.598    0.657    0.684    0.714    0.762 1.005
## p[473]       0.596   0.046    0.505    0.565    0.596    0.628    0.686 1.007
## p[474]       0.536   0.034    0.470    0.513    0.535    0.559    0.602 1.002
## p[475]       0.765   0.032    0.701    0.744    0.767    0.788    0.823 1.001
## p[476]       0.704   0.042    0.615    0.677    0.706    0.734    0.782 1.002
## p[477]       0.562   0.037    0.490    0.537    0.562    0.587    0.632 1.001
## p[478]       0.233   0.035    0.172    0.208    0.231    0.255    0.309 1.002
## p[479]       0.668   0.047    0.574    0.637    0.670    0.700    0.760 1.010
## p[480]       0.749   0.029    0.689    0.730    0.750    0.769    0.801 1.002
## p[481]       0.498   0.046    0.409    0.466    0.499    0.529    0.590 1.003
## p[482]       0.247   0.039    0.177    0.219    0.246    0.271    0.334 1.001
## p[483]       0.513   0.042    0.429    0.484    0.514    0.542    0.593 1.001
## p[484]       0.740   0.034    0.671    0.718    0.741    0.763    0.802 1.001
## p[485]       0.372   0.044    0.291    0.340    0.371    0.401    0.466 1.005
## p[486]       0.744   0.034    0.673    0.721    0.745    0.767    0.805 1.001
## p[487]       0.352   0.041    0.276    0.324    0.352    0.380    0.437 1.001
## p[488]       0.481   0.041    0.401    0.454    0.482    0.509    0.559 1.001
## p[489]       0.251   0.035    0.190    0.226    0.250    0.272    0.326 1.006
## p[490]       0.461   0.042    0.380    0.433    0.461    0.490    0.541 1.001
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## p[491]       0.471   0.043    0.387    0.442    0.472    0.500    0.553 1.001
## p[492]       0.502   0.040    0.423    0.474    0.502    0.529    0.579 1.001
## p[493]       0.199   0.038    0.133    0.172    0.197    0.222    0.281 1.012
## p[494]       0.717   0.058    0.595    0.680    0.718    0.758    0.822 1.001
## p[495]       0.483   0.043    0.398    0.454    0.484    0.512    0.569 1.004
## p[496]       0.338   0.039    0.267    0.312    0.336    0.364    0.416 1.001
## p[497]       0.502   0.044    0.415    0.473    0.503    0.531    0.590 1.001
## p[498]       0.493   0.044    0.411    0.463    0.492    0.523    0.579 1.007
## p[499]       0.643   0.033    0.578    0.622    0.644    0.666    0.703 1.001
## p[500]       0.401   0.062    0.285    0.359    0.398    0.443    0.526 1.001
## p[501]       0.658   0.058    0.537    0.620    0.658    0.698    0.764 1.001
## p[502]       0.668   0.037    0.596    0.644    0.669    0.694    0.739 1.001
## p[503]       0.594   0.047    0.502    0.562    0.594    0.626    0.685 1.007
## p[504]       0.586   0.049    0.489    0.554    0.587    0.619    0.682 1.001
## p[505]       0.301   0.031    0.244    0.280    0.299    0.321    0.366 1.006
## p[506]       0.347   0.045    0.266    0.316    0.346    0.376    0.437 1.001
## p[507]       0.279   0.035    0.214    0.255    0.278    0.302    0.354 1.011
## p[508]       0.287   0.033    0.226    0.264    0.285    0.308    0.355 1.004
## p[509]       0.422   0.029    0.368    0.402    0.421    0.441    0.480 1.004
## p[510]       0.588   0.044    0.507    0.559    0.587    0.619    0.671 1.017
## p[511]       0.577   0.040    0.498    0.551    0.578    0.605    0.653 1.001
## p[512]       0.363   0.042    0.287    0.336    0.362    0.391    0.449 1.001
## p[513]       0.254   0.035    0.192    0.230    0.253    0.276    0.332 1.008
## p[514]       0.332   0.037    0.265    0.307    0.331    0.356    0.407 1.003
## p[515]       0.346   0.038    0.278    0.320    0.345    0.371    0.425 1.001
## p[516]       0.467   0.044    0.383    0.437    0.466    0.496    0.554 1.004
## p[517]       0.322   0.045    0.239    0.290    0.321    0.352    0.415 1.001
## p[518]       0.764   0.049    0.662    0.733    0.767    0.800    0.849 1.004
## p[519]       0.323   0.056    0.223    0.284    0.321    0.360    0.441 1.001
## p[520]       0.545   0.048    0.451    0.512    0.544    0.580    0.637 1.001
## p[521]       0.287   0.036    0.223    0.262    0.286    0.311    0.364 1.002
## p[522]       0.691   0.040    0.608    0.665    0.691    0.719    0.764 1.004
## p[523]       0.291   0.044    0.211    0.261    0.289    0.318    0.386 1.011
## p[524]       0.245   0.034    0.185    0.221    0.244    0.266    0.319 1.005
## p[525]       0.871   0.028    0.809    0.853    0.873    0.890    0.918 1.006
## p[526]       0.393   0.046    0.307    0.362    0.394    0.424    0.482 1.002
## p[527]       0.361   0.030    0.305    0.340    0.361    0.381    0.423 1.006
## p[528]       0.470   0.061    0.351    0.427    0.470    0.513    0.589 1.004
## p[529]       0.284   0.031    0.228    0.262    0.283    0.304    0.348 1.006
## p[530]       0.499   0.046    0.413    0.468    0.500    0.531    0.588 1.006
## p[531]       0.326   0.032    0.271    0.304    0.325    0.347    0.390 1.003
## p[532]       0.273   0.033    0.212    0.249    0.272    0.295    0.344 1.009
## p[533]       0.321   0.034    0.257    0.297    0.320    0.343    0.393 1.006
## p[534]       0.325   0.034    0.261    0.301    0.324    0.347    0.395 1.007
## p[535]       0.324   0.034    0.260    0.300    0.323    0.346    0.394 1.006
## p[536]       0.390   0.046    0.303    0.359    0.390    0.421    0.479 1.001
## p[537]       0.412   0.046    0.326    0.381    0.412    0.443    0.502 1.005
## p[538]       0.313   0.028    0.262    0.294    0.312    0.332    0.372 1.004
## p[539]       0.791   0.030    0.728    0.772    0.793    0.812    0.845 1.007
## p[540]       0.568   0.041    0.488    0.541    0.568    0.596    0.648 1.002
## p[541]       0.655   0.037    0.580    0.630    0.655    0.681    0.725 1.004
## p[542]       0.433   0.036    0.363    0.408    0.431    0.457    0.505 1.002
## p[543]       0.261   0.050    0.174    0.228    0.257    0.293    0.366 1.001
## p[544]       0.545   0.041    0.462    0.518    0.546    0.573    0.626 1.003
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## p[545]       0.573   0.041     0.491     0.546     0.574     0.601     0.651 1.002
## p[546]       0.214   0.038     0.146     0.189     0.212     0.238     0.294 1.002
## p[547]       0.564   0.037     0.492     0.539     0.563     0.590     0.637 1.006
## p[548]       0.741   0.041     0.656     0.712     0.743     0.770     0.813 1.025
## p[549]       0.829   0.040     0.745     0.805     0.833     0.857     0.898 1.011
## p[550]       0.670   0.037     0.594     0.645     0.671     0.696     0.741 1.005
## p[551]       0.589   0.062     0.462     0.549     0.589     0.632     0.703 1.001
## p[552]       0.407   0.045     0.320     0.376     0.406     0.438     0.495 1.001
## p[553]       0.381   0.044     0.299     0.351     0.380     0.411     0.471 1.015
## p[554]       0.463   0.042     0.382     0.434     0.463     0.492     0.543 1.001
## p[555]       0.265   0.038     0.198     0.238     0.263     0.288     0.345 1.011
## p[556]       0.789   0.035     0.715     0.765     0.790     0.813     0.853 1.002
## p[557]       0.598   0.041     0.519     0.570     0.597     0.626     0.680 1.005
## p[558]       0.579   0.057     0.471     0.541     0.580     0.619     0.687 1.004
## p[559]       0.321   0.033     0.262     0.298     0.320     0.343     0.387 1.002
## p[560]       0.635   0.051     0.534     0.603     0.636     0.669     0.729 1.007
## p[561]       0.267   0.038     0.199     0.240     0.265     0.291     0.348 1.012
## p[562]       0.687   0.053     0.578     0.652     0.689     0.724     0.786 1.002
## p[563]       0.461   0.049     0.367     0.428     0.461     0.492     0.560 1.013
## p[564]       0.696   0.036     0.621     0.671     0.697     0.720     0.764 1.004
## p[565]       0.280   0.031     0.226     0.259     0.279     0.301     0.344 1.005
## p[566]       0.484   0.040     0.404     0.457     0.486     0.511     0.561 1.001
## p[567]       0.362   0.035     0.295     0.338     0.362     0.386     0.435 1.012
## p[568]       0.317   0.038     0.245     0.291     0.316     0.343     0.395 1.005
## p[569]       0.332   0.035     0.266     0.307     0.330     0.355     0.405 1.009
## p[570]       0.363   0.039     0.290     0.336     0.362     0.388     0.441 1.006
## p[571]       0.614   0.036     0.542     0.590     0.616     0.638     0.682 1.001
## p[572]       0.426   0.046     0.339     0.394     0.426     0.457     0.523 1.008
## p[573]       0.352   0.032     0.291     0.329     0.352     0.374     0.419 1.009
## p[574]       0.657   0.039     0.579     0.631     0.658     0.686     0.730 1.006
## p[575]       0.402   0.040     0.327     0.376     0.402     0.430     0.481 1.001
## p[576]       0.252   0.039     0.184     0.225     0.251     0.276     0.338 1.002
## p[577]       0.321   0.046     0.237     0.289     0.320     0.351     0.414 1.001
## p[578]       0.358   0.046     0.270     0.327     0.356     0.387     0.451 1.006
## p[579]       0.804   0.047     0.700     0.776     0.809     0.838     0.884 1.013
## p[580]       0.487   0.060     0.370     0.445     0.486     0.529     0.604 1.006
## p[581]       0.478   0.041     0.397     0.451     0.479     0.506     0.557 1.001
## p[582]       0.258   0.033     0.199     0.234     0.256     0.279     0.324 1.003
## p[583]       0.292   0.032     0.234     0.270     0.290     0.313     0.360 1.004
## p[584]       0.522   0.040     0.442     0.495     0.522     0.551     0.599 1.001
## p[585]       0.660   0.037     0.586     0.636     0.661     0.686     0.730 1.002
## p[586]       0.496   0.043     0.416     0.467     0.495     0.526     0.580 1.006
## p[587]       0.623   0.058     0.505     0.585     0.625     0.665     0.731 1.002
## p[588]       0.273   0.033     0.212     0.249     0.272     0.295     0.344 1.009
## p[589]       0.833   0.032     0.766     0.813     0.835     0.856     0.887 1.005
## p[590]       0.251   0.033     0.190     0.227     0.249     0.273     0.319 1.002
## p[591]       0.376   0.037     0.306     0.350     0.375     0.399     0.451 1.001
## p[592]       0.549   0.043     0.466     0.519     0.548     0.580     0.632 1.009
## p[593]       0.363   0.048     0.274     0.330     0.362     0.395     0.460 1.015
## p[594]       0.566   0.060     0.447     0.526     0.567     0.609     0.680 1.002
## p[595]       0.568   0.036     0.498     0.544     0.568     0.593     0.637 1.001
## p[596]       0.417   0.044     0.333     0.387     0.416     0.447     0.504 1.001
## p[597]       0.568   0.041     0.488     0.541     0.568     0.596     0.648 1.002
## p[598]       0.309   0.034     0.247     0.285     0.307     0.332     0.378 1.003
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## p[599]       0.426   0.039    0.353    0.399    0.425    0.451    0.503 1.004
## p[600]       0.358   0.057    0.251    0.318    0.356    0.397    0.471 1.008
## p[601]       0.630   0.047    0.532    0.598    0.631    0.663    0.719 1.005
## p[602]       0.449   0.048    0.357    0.416    0.450    0.482    0.542 1.001
## p[603]       0.282   0.031    0.227    0.260    0.281    0.302    0.346 1.005
## p[604]       0.251   0.033    0.190    0.227    0.249    0.273    0.319 1.002
## p[605]       0.474   0.042    0.391    0.446    0.475    0.502    0.554 1.001
## p[606]       0.388   0.037    0.320    0.362    0.387    0.413    0.464 1.003
## p[607]       0.361   0.042    0.284    0.333    0.359    0.388    0.447 1.001
## p[608]       0.438   0.055    0.334    0.399    0.439    0.476    0.548 1.002
## p[609]       0.501   0.044    0.417    0.472    0.501    0.532    0.586 1.009
## p[610]       0.442   0.038    0.369    0.418    0.442    0.468    0.515 1.001
## p[611]       0.689   0.041    0.604    0.662    0.688    0.717    0.764 1.004
## p[612]       0.485   0.060    0.368    0.443    0.485    0.527    0.602 1.006
## p[613]       0.684   0.042    0.601    0.656    0.684    0.712    0.764 1.003
## p[614]       0.670   0.039    0.591    0.645    0.672    0.696    0.743 1.004
## p[615]       0.773   0.029    0.713    0.754    0.774    0.793    0.823 1.008
## p[616]       0.313   0.033    0.251    0.289    0.312    0.336    0.380 1.003
## p[617]       0.594   0.039    0.515    0.568    0.594    0.620    0.669 1.003
## p[618]       0.558   0.046    0.468    0.528    0.558    0.589    0.645 1.001
## p[619]       0.515   0.054    0.410    0.478    0.515    0.551    0.622 1.010
## p[620]       0.540   0.065    0.406    0.495    0.539    0.586    0.661 1.006
## p[621]       0.599   0.049    0.502    0.566    0.600    0.633    0.689 1.005
## p[622]       0.822   0.032    0.753    0.802    0.824    0.844    0.880 1.001
## p[623]       0.305   0.034    0.242    0.281    0.304    0.328    0.375 1.002
## p[624]       0.598   0.038    0.525    0.573    0.598    0.625    0.670 1.001
## p[625]       0.726   0.040    0.647    0.700    0.728    0.753    0.800 1.001
## p[626]       0.326   0.035    0.261    0.301    0.324    0.349    0.401 1.013
## p[627]       0.519   0.042    0.434    0.491    0.519    0.546    0.600 1.002
## p[628]       0.324   0.032    0.267    0.301    0.323    0.345    0.388 1.003
## p[629]       0.330   0.054    0.233    0.293    0.327    0.365    0.438 1.001
## p[630]       0.397   0.036    0.326    0.372    0.397    0.421    0.468 1.003
## p[631]       0.834   0.034    0.762    0.812    0.836    0.858    0.894 1.001
## p[632]       0.351   0.032    0.291    0.328    0.350    0.372    0.418 1.008
## p[633]       0.319   0.041    0.243    0.291    0.318    0.346    0.406 1.017
## p[634]       0.579   0.046    0.483    0.548    0.579    0.610    0.664 1.007
## p[635]       0.864   0.035    0.789    0.843    0.868    0.889    0.923 1.014
## p[636]       0.651   0.058    0.535    0.612    0.653    0.691    0.760 1.003
## p[637]       0.824   0.041    0.737    0.799    0.827    0.853    0.894 1.006
## p[638]       0.248   0.030    0.194    0.226    0.246    0.267    0.312 1.002
## p[639]       0.584   0.063    0.458    0.541    0.586    0.626    0.704 1.007
## p[640]       0.662   0.039    0.582    0.637    0.663    0.688    0.734 1.007
## p[641]       0.317   0.040    0.246    0.291    0.317    0.343    0.399 1.003
## p[642]       0.719   0.034    0.649    0.696    0.720    0.743    0.782 1.006
## p[643]       0.491   0.029    0.434    0.471    0.491    0.511    0.547 1.003
## p[644]       0.588   0.045    0.500    0.558    0.588    0.618    0.671 1.004
## p[645]       0.290   0.029    0.238    0.270    0.289    0.309    0.349 1.003
## p[646]       0.880   0.025    0.825    0.865    0.882    0.897    0.922 1.006
## p[647]       0.332   0.055    0.232    0.295    0.328    0.368    0.445 1.001
## p[648]       0.572   0.043    0.488    0.544    0.572    0.602    0.657 1.002
## p[649]       0.619   0.042    0.534    0.590    0.619    0.649    0.697 1.004
## p[650]       0.908   0.031    0.836    0.890    0.913    0.929    0.954 1.002
## p[651]       0.628   0.056    0.513    0.589    0.630    0.669    0.734 1.012
## p[652]       0.494   0.042    0.411    0.466    0.495    0.523    0.575 1.001
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## p[653]       0.775   0.035    0.702    0.753    0.778    0.800    0.837 1.014
## p[654]       0.637   0.061    0.509    0.596    0.638    0.680    0.749 1.008
## p[655]       0.708   0.043    0.621    0.679    0.709    0.738    0.787 1.001
## p[656]       0.815   0.033    0.746    0.794    0.816    0.838    0.876 1.001
## p[657]       0.760   0.033    0.693    0.739    0.762    0.783    0.818 1.014
## p[658]       0.482   0.035    0.415    0.458    0.481    0.506    0.552 1.004
## p[659]       0.660   0.044    0.572    0.632    0.660    0.690    0.743 1.001
## p[660]       0.382   0.061    0.268    0.340    0.380    0.421    0.504 1.002
## p[661]       0.710   0.038    0.635    0.685    0.711    0.737    0.785 1.001
## p[662]       0.770   0.028    0.713    0.752    0.773    0.790    0.820 1.002
## p[663]       0.621   0.055    0.509    0.583    0.623    0.661    0.723 1.007
## p[664]       0.624   0.058    0.506    0.584    0.626    0.665    0.731 1.013
## p[665]       0.370   0.041    0.293    0.342    0.371    0.397    0.451 1.002
## p[666]       0.551   0.041    0.469    0.524    0.553    0.578    0.630 1.002
## p[667]       0.689   0.038    0.612    0.664    0.690    0.715    0.759 1.007
## p[668]       0.782   0.034    0.709    0.759    0.784    0.806    0.844 1.004
## p[669]       0.495   0.041    0.413    0.467    0.496    0.524    0.575 1.001
## p[670]       0.678   0.036    0.606    0.655    0.679    0.703    0.746 1.003
## p[671]       0.743   0.029    0.682    0.724    0.744    0.764    0.794 1.004
## p[672]       0.567   0.053    0.468    0.530    0.567    0.604    0.673 1.012
## p[673]       0.813   0.031    0.748    0.794    0.815    0.834    0.869 1.001
## p[674]       0.558   0.038    0.482    0.533    0.560    0.584    0.628 1.001
## p[675]       0.222   0.032    0.165    0.199    0.220    0.242    0.291 1.004
## p[676]       0.726   0.040    0.645    0.699    0.727    0.754    0.799 1.018
## p[677]       0.636   0.031    0.572    0.616    0.636    0.657    0.696 1.004
## p[678]       0.571   0.046    0.478    0.541    0.572    0.602    0.659 1.001
## p[679]       0.570   0.036    0.501    0.546    0.569    0.595    0.642 1.004
## p[680]       0.362   0.042    0.282    0.333    0.362    0.390    0.445 1.001
## p[681]       0.713   0.055    0.599    0.678    0.714    0.753    0.813 1.003
## p[682]       0.457   0.042    0.374    0.428    0.457    0.486    0.537 1.001
## p[683]       0.479   0.069    0.345    0.432    0.477    0.526    0.612 1.001
## p[684]       0.659   0.039    0.581    0.633    0.660    0.686    0.730 1.006
## p[685]       0.446   0.032    0.385    0.425    0.445    0.469    0.512 1.001
## p[686]       0.730   0.038    0.653    0.705    0.731    0.757    0.803 1.001
## p[687]       0.644   0.054    0.534    0.607    0.646    0.682    0.743 1.005
## p[688]       0.547   0.050    0.448    0.513    0.547    0.583    0.640 1.004
## p[689]       0.633   0.051    0.532    0.601    0.635    0.668    0.728 1.007
## p[690]       0.417   0.046    0.328    0.385    0.417    0.448    0.508 1.006
## p[691]       0.567   0.042    0.484    0.538    0.568    0.597    0.646 1.001
## p[692]       0.491   0.038    0.417    0.466    0.490    0.517    0.568 1.001
## p[693]       0.478   0.034    0.411    0.455    0.478    0.503    0.545 1.005
## p[694]       0.664   0.037    0.591    0.640    0.665    0.690    0.735 1.001
## p[695]       0.388   0.044    0.304    0.358    0.388    0.417    0.479 1.001
## p[696]       0.544   0.045    0.458    0.513    0.543    0.576    0.630 1.010
## p[697]       0.491   0.029    0.434    0.471    0.491    0.511    0.547 1.003
## p[698]       0.409   0.057    0.302    0.371    0.406    0.446    0.523 1.001
## p[699]       0.483   0.036    0.413    0.459    0.483    0.508    0.553 1.006
## p[700]       0.653   0.065    0.523    0.610    0.656    0.697    0.771 1.004
## p[701]       0.493   0.046    0.406    0.462    0.494    0.524    0.587 1.007
## p[702]       0.610   0.039    0.532    0.584    0.611    0.637    0.684 1.005
## p[703]       0.804   0.030    0.741    0.784    0.806    0.824    0.858 1.002
## p[704]       0.660   0.035    0.587    0.637    0.661    0.684    0.726 1.002
## p[705]       0.493   0.048    0.398    0.461    0.493    0.525    0.585 1.003
## p[706]       0.637   0.035    0.566    0.613    0.637    0.662    0.704 1.009
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## p[707]      0.592  0.034    0.524    0.570    0.592    0.615    0.656 1.005
## p[708]      0.415  0.040    0.338    0.388    0.415    0.441    0.496 1.011
## p[709]      0.798  0.043    0.706    0.771    0.800    0.828    0.873 1.007
## p[710]      0.911  0.030    0.840    0.893    0.915    0.932    0.957 1.007
## p[711]      0.806  0.030    0.744    0.786    0.807    0.826    0.861 1.002
## p[712]      0.486  0.040    0.407    0.459    0.487    0.513    0.563 1.001
## p[713]      0.497  0.038    0.423    0.472    0.496    0.523    0.575 1.002
## p[714]      0.564  0.048    0.465    0.531    0.564    0.597    0.658 1.006
## p[715]      0.611  0.043    0.526    0.582    0.612    0.640    0.690 1.002
## p[716]      0.963  0.015    0.927    0.956    0.965    0.973    0.984 1.025
## p[717]      0.404  0.031    0.346    0.382    0.403    0.424    0.466 1.005
## p[718]      0.479  0.062    0.356    0.439    0.480    0.520    0.596 1.005
## p[719]      0.410  0.045    0.323    0.380    0.410    0.440    0.500 1.001
## p[720]      0.376  0.059    0.268    0.338    0.374    0.413    0.496 1.001
## p[721]      0.411  0.044    0.328    0.381    0.411    0.440    0.498 1.004
## p[722]      0.531  0.066    0.400    0.488    0.530    0.576    0.657 1.001
## p[723]      0.379  0.039    0.305    0.353    0.379    0.405    0.458 1.001
## p[724]      0.397  0.038    0.324    0.371    0.396    0.422    0.473 1.005
## p[725]      0.777  0.031    0.710    0.756    0.778    0.799    0.832 1.002
## p[726]      0.825  0.032    0.755    0.804    0.827    0.847    0.883 1.001
## p[727]      0.603  0.037    0.530    0.578    0.604    0.628    0.673 1.001
## p[728]      0.389  0.039    0.315    0.363    0.389    0.415    0.471 1.005
## p[729]      0.537  0.044    0.453    0.507    0.536    0.566    0.623 1.004
## p[730]      0.366  0.042    0.288    0.338    0.367    0.393    0.447 1.001
## p[731]      0.291  0.036    0.225    0.266    0.289    0.314    0.368 1.009
## p[732]      0.270  0.032    0.213    0.247    0.268    0.291    0.336 1.003
## p[733]      0.500  0.040    0.420    0.472    0.501    0.527    0.578 1.001
## p[734]      0.605  0.052    0.502    0.571    0.606    0.643    0.706 1.007
## p[735]      0.342  0.041    0.266    0.314    0.342    0.368    0.423 1.001
## p[736]      0.357  0.058    0.246    0.318    0.353    0.393    0.475 1.001
## p[737]      0.464  0.044    0.378    0.435    0.465    0.494    0.549 1.002
## p[738]      0.280  0.035    0.215    0.256    0.280    0.303    0.355 1.012
## p[739]      0.588  0.045    0.500    0.558    0.588    0.618    0.671 1.004
## p[740]      0.420  0.038    0.348    0.395    0.420    0.446    0.496 1.004
## p[741]      0.319  0.041    0.243    0.291    0.318    0.346    0.406 1.017
## p[742]      0.385  0.047    0.295    0.353    0.384    0.416    0.477 1.001
## p[743]      0.420  0.044    0.337    0.390    0.419    0.449    0.506 1.001
## p[744]      0.350  0.039    0.276    0.324    0.349    0.375    0.430 1.007
## p[745]      0.736  0.037    0.662    0.711    0.738    0.762    0.801 1.015
## p[746]      0.319  0.033    0.258    0.297    0.318    0.341    0.391 1.011
## p[747]      0.211  0.035    0.148    0.186    0.208    0.231    0.288 1.012
## p[748]      0.282  0.035    0.216    0.257    0.281    0.305    0.355 1.012
## p[749]      0.458  0.042    0.376    0.430    0.459    0.487    0.538 1.001
## p[750]      0.440  0.036    0.369    0.416    0.439    0.465    0.513 1.003
## p[751]      0.514  0.048    0.422    0.483    0.514    0.547    0.606 1.003
## p[752]      0.764  0.031    0.698    0.744    0.765    0.786    0.819 1.013
## p[753]      0.472  0.068    0.339    0.427    0.471    0.519    0.608 1.001
## p[754]      0.504  0.047    0.408    0.472    0.504    0.536    0.597 1.004
## p[755]      0.572  0.043    0.489    0.543    0.572    0.602    0.654 1.008
## p[756]      0.586  0.048    0.489    0.555    0.587    0.619    0.678 1.008
## p[757]      0.597  0.059    0.478    0.557    0.601    0.638    0.706 1.014
## p[758]      0.467  0.068    0.335    0.421    0.465    0.513    0.600 1.001
## p[759]      0.636  0.031    0.572    0.615    0.637    0.658    0.694 1.001
## p[760]      0.778  0.034    0.706    0.755    0.780    0.802    0.837 1.014
```

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## p[761]       0.799   0.036    0.720    0.776    0.801    0.824    0.864 1.004
## p[762]       0.758   0.033    0.689    0.736    0.760    0.782    0.818 1.015
## p[763]       0.453   0.036    0.386    0.427    0.452    0.478    0.524 1.005
## p[764]       0.588   0.034    0.523    0.564    0.588    0.612    0.654 1.008
## p[765]       0.334   0.031    0.280    0.312    0.333    0.355    0.397 1.004
## p[766]       0.789   0.038    0.708    0.763    0.791    0.816    0.855 1.014
## p[767]       0.735   0.038    0.658    0.710    0.737    0.761    0.806 1.008
## p[768]       0.536   0.047    0.444    0.505    0.536    0.568    0.627 1.004
## p[769]       0.574   0.058    0.458    0.536    0.575    0.615    0.686 1.005
## p[770]       0.392   0.043    0.311    0.364    0.392    0.420    0.480 1.001
## p[771]       0.716   0.034    0.646    0.694    0.716    0.740    0.777 1.004
## p[772]       0.653   0.037    0.578    0.628    0.654    0.679    0.725 1.004
## p[773]       0.632   0.049    0.534    0.600    0.633    0.666    0.723 1.005
## p[774]       0.470   0.048    0.377    0.438    0.470    0.503    0.564 1.003
## p[775]       0.314   0.048    0.225    0.281    0.313    0.345    0.414 1.001
## p[776]       0.255   0.036    0.190    0.229    0.254    0.278    0.330 1.018
## p[777]       0.632   0.042    0.545    0.602    0.633    0.662    0.711 1.002
## p[778]       0.442   0.047    0.350    0.410    0.441    0.474    0.534 1.001
## p[779]       0.414   0.046    0.327    0.382    0.414    0.445    0.503 1.005
## p[780]       0.594   0.058    0.477    0.555    0.596    0.634    0.704 1.004
## p[781]       0.329   0.035    0.263    0.304    0.327    0.352    0.401 1.008
## p[782]       0.652   0.041    0.569    0.625    0.653    0.680    0.730 1.010
## p[783]       0.376   0.040    0.301    0.349    0.377    0.402    0.454 1.003
## p[784]       0.621   0.033    0.555    0.598    0.622    0.643    0.682 1.001
## p[785]       0.781   0.041    0.694    0.754    0.784    0.811    0.852 1.016
## p[786]       0.375   0.040    0.301    0.348    0.375    0.401    0.455 1.001
## p[787]       0.654   0.041    0.571    0.627    0.655    0.681    0.731 1.010
## p[788]       0.851   0.037    0.768    0.829    0.855    0.878    0.914 1.021
## p[789]       0.732   0.037    0.657    0.708    0.734    0.757    0.801 1.001
## p[790]       0.583   0.049    0.483    0.551    0.584    0.617    0.678 1.008
## p[791]       0.417   0.043    0.335    0.387    0.416    0.446    0.502 1.005
## p[792]       0.445   0.037    0.373    0.420    0.444    0.470    0.518 1.004
## p[793]       0.642   0.032    0.577    0.621    0.643    0.665    0.702 1.001
## p[794]       0.707   0.038    0.630    0.682    0.708    0.733    0.777 1.003
## p[795]       0.251   0.035    0.190    0.226    0.250    0.272    0.326 1.006
## p[796]       0.626   0.046    0.534    0.594    0.627    0.658    0.711 1.003
## p[797]       0.325   0.034    0.261    0.301    0.324    0.347    0.395 1.007
## p[798]       0.360   0.030    0.304    0.339    0.359    0.380    0.422 1.006
## p[799]       0.552   0.041    0.472    0.524    0.550    0.579    0.632 1.002
## p[800]       0.422   0.039    0.345    0.396    0.421    0.448    0.499 1.007
## p[801]       0.743   0.041    0.659    0.715    0.744    0.771    0.816 1.019
## p[802]       0.823   0.032    0.754    0.803    0.825    0.845    0.882 1.001
## p[803]       0.314   0.033    0.252    0.290    0.313    0.337    0.381 1.004
## p[804]       0.314   0.038    0.242    0.288    0.313    0.339    0.395 1.016
## p[805]       0.454   0.043    0.369    0.424    0.454    0.482    0.534 1.001
## p[806]       0.378   0.042    0.300    0.349    0.379    0.406    0.464 1.011
## p[807]       0.356   0.044    0.274    0.326    0.356    0.385    0.443 1.001
## p[808]       0.590   0.035    0.522    0.567    0.589    0.614    0.658 1.001
## p[809]       0.675   0.042    0.588    0.647    0.676    0.705    0.752 1.002
## p[810]       0.908   0.020    0.864    0.896    0.910    0.922    0.941 1.010
## p[811]       0.324   0.048    0.233    0.290    0.322    0.355    0.423 1.002
## p[812]       0.745   0.045    0.645    0.715    0.747    0.778    0.826 1.005
## p[813]       0.506   0.060    0.391    0.465    0.506    0.548    0.623 1.001
## p[814]       0.758   0.034    0.686    0.736    0.759    0.782    0.819 1.008
```

```
## p[815]      0.755   0.033    0.685    0.734    0.756    0.778    0.817 1.001
## p[816]      0.309   0.034    0.247    0.285    0.307    0.332    0.378 1.003
## p[817]      0.413   0.056    0.304    0.376    0.412    0.451    0.524 1.007
## deviance 1022.500   3.681 1017.324 1019.773 1021.824 1024.588 1031.128 1.007
##          n.eff
## beta1       54
## beta2      120
## beta3     2200
## beta4      640
## beta5     1100
## beta6      710
## beta7       96
## p[1]       730
## p[2]      1100
## p[3]       570
## p[4]       260
## p[5]       550
## p[6]      2200
## p[7]      1600
## p[8]       630
## p[9]      1500
## p[10]      630
## p[11]      460
## p[12]      280
## p[13]      570
## p[14]      320
## p[15]     2200
## p[16]     2200
## p[17]     1700
## p[18]     2200
## p[19]      160
## p[20]      380
## p[21]      210
## p[22]      180
## p[23]      710
## p[24]     2200
## p[25]      560
## p[26]     2200
## p[27]     2200
## p[28]      420
## p[29]      410
## p[30]      380
## p[31]      100
## p[32]      140
## p[33]      920
## p[34]     2200
## p[35]      390
## p[36]      150
## p[37]      300
## p[38]      310
## p[39]      190
## p[40]     1000
## p[41]     2200
## p[42]     1700
```

```
## p[43]       1400
## p[44]        230
## p[45]        690
## p[46]        270
## p[47]       2200
## p[48]        140
## p[49]        540
## p[50]        210
## p[51]       2200
## p[52]       2200
## p[53]       2200
## p[54]        210
## p[55]        200
## p[56]        490
## p[57]         76
## p[58]       2100
## p[59]        370
## p[60]        200
## p[61]       2200
## p[62]         73
## p[63]       2200
## p[64]        600
## p[65]       2200
## p[66]        240
## p[67]       2200
## p[68]       2200
## p[69]        120
## p[70]        360
## p[71]       2200
## p[72]        170
## p[73]       2200
## p[74]       2200
## p[75]        370
## p[76]        480
## p[77]       2200
## p[78]        800
## p[79]        370
## p[80]        300
## p[81]        170
## p[82]        480
## p[83]       1200
## p[84]       2200
## p[85]       2200
## p[86]       2200
## p[87]        360
## p[88]       2200
## p[89]        200
## p[90]       2200
## p[91]        150
## p[92]        430
## p[93]        630
## p[94]       1700
## p[95]       2200
## p[96]        920
```

```
## p[97]        930
## p[98]       2200
## p[99]       2200
## p[100]       340
## p[101]        88
## p[102]       300
## p[103]       250
## p[104]      2200
## p[105]      2100
## p[106]       100
## p[107]       100
## p[108]      2200
## p[109]       790
## p[110]      2200
## p[111]       530
## p[112]       930
## p[113]      2200
## p[114]      2200
## p[115]      2200
## p[116]       710
## p[117]      2200
## p[118]      2200
## p[119]      2200
## p[120]      2200
## p[121]      2200
## p[122]      2200
## p[123]       180
## p[124]       240
## p[125]       830
## p[126]       290
## p[127]      2200
## p[128]      2200
## p[129]       300
## p[130]      2200
## p[131]      1100
## p[132]       260
## p[133]       240
## p[134]       350
## p[135]       330
## p[136]      2200
## p[137]      2200
## p[138]      1300
## p[139]      2200
## p[140]      2200
## p[141]       790
## p[142]      2200
## p[143]      2200
## p[144]      2200
## p[145]      1400
## p[146]      2200
## p[147]       110
## p[148]      1200
## p[149]       130
## p[150]       190
```

```
## p[151]     1200
## p[152]     2000
## p[153]      230
## p[154]      720
## p[155]      380
## p[156]      410
## p[157]      210
## p[158]      240
## p[159]      380
## p[160]     2200
## p[161]     2200
## p[162]      150
## p[163]      240
## p[164]      980
## p[165]     2200
## p[166]      280
## p[167]     2200
## p[168]     2200
## p[169]      240
## p[170]      110
## p[171]     1300
## p[172]     2200
## p[173]      250
## p[174]     2200
## p[175]      520
## p[176]      430
## p[177]     2200
## p[178]      170
## p[179]      230
## p[180]      420
## p[181]      380
## p[182]      150
## p[183]     1100
## p[184]      230
## p[185]     1500
## p[186]      320
## p[187]      190
## p[188]     2200
## p[189]      290
## p[190]      190
## p[191]      650
## p[192]     2200
## p[193]     2200
## p[194]      760
## p[195]      740
## p[196]      260
## p[197]      400
## p[198]      150
## p[199]      180
## p[200]      790
## p[201]     2000
## p[202]     2200
## p[203]     2200
## p[204]     2200
```

```
## p[205]     2200
## p[206]     2200
## p[207]      540
## p[208]      420
## p[209]      270
## p[210]     2200
## p[211]      220
## p[212]      230
## p[213]      430
## p[214]      240
## p[215]     2200
## p[216]      850
## p[217]     2200
## p[218]      150
## p[219]     2200
## p[220]      290
## p[221]       98
## p[222]     2200
## p[223]      890
## p[224]     2200
## p[225]     1700
## p[226]     1300
## p[227]      120
## p[228]     2200
## p[229]      170
## p[230]      130
## p[231]     2200
## p[232]      950
## p[233]     2200
## p[234]      760
## p[235]      190
## p[236]      130
## p[237]      300
## p[238]     1100
## p[239]      210
## p[240]     2200
## p[241]      120
## p[242]      270
## p[243]      520
## p[244]     2200
## p[245]     1700
## p[246]      280
## p[247]     2200
## p[248]     1400
## p[249]     2200
## p[250]      380
## p[251]     1600
## p[252]     2200
## p[253]     2200
## p[254]     1100
## p[255]      200
## p[256]      150
## p[257]      100
## p[258]      200
```

```
## p[259]      88
## p[260]     210
## p[261]     300
## p[262]     140
## p[263]     110
## p[264]     590
## p[265]     120
## p[266]     170
## p[267]    1400
## p[268]     470
## p[269]     220
## p[270]     280
## p[271]    2200
## p[272]     790
## p[273]     300
## p[274]    2200
## p[275]      90
## p[276]    2200
## p[277]    1700
## p[278]     750
## p[279]    2200
## p[280]     430
## p[281]     150
## p[282]    2200
## p[283]     140
## p[284]    2200
## p[285]    2200
## p[286]     370
## p[287]     550
## p[288]     360
## p[289]    2200
## p[290]     340
## p[291]     390
## p[292]    1100
## p[293]     410
## p[294]    2200
## p[295]     120
## p[296]     490
## p[297]    2200
## p[298]    1100
## p[299]    2200
## p[300]     320
## p[301]     160
## p[302]     120
## p[303]    1600
## p[304]     180
## p[305]     160
## p[306]    1900
## p[307]     550
## p[308]     100
## p[309]     340
## p[310]     490
## p[311]     140
## p[312]     860
```

```
## p[313]     2200
## p[314]     2200
## p[315]      110
## p[316]     2200
## p[317]     2200
## p[318]      100
## p[319]      190
## p[320]      640
## p[321]       87
## p[322]     1700
## p[323]      380
## p[324]      150
## p[325]     1100
## p[326]      360
## p[327]      490
## p[328]     2200
## p[329]     2200
## p[330]     2200
## p[331]      660
## p[332]      990
## p[333]     1100
## p[334]      180
## p[335]      180
## p[336]      150
## p[337]     2000
## p[338]      280
## p[339]      120
## p[340]      410
## p[341]      400
## p[342]     2200
## p[343]      970
## p[344]      110
## p[345]      420
## p[346]      480
## p[347]      170
## p[348]      990
## p[349]      110
## p[350]      610
## p[351]     2200
## p[352]      220
## p[353]      240
## p[354]      260
## p[355]      360
## p[356]      320
## p[357]      270
## p[358]     2200
## p[359]      570
## p[360]       91
## p[361]      860
## p[362]     2200
## p[363]      310
## p[364]       97
## p[365]      740
## p[366]     2200
```

```
## p[367]    180
## p[368]   2200
## p[369]   1600
## p[370]   2200
## p[371]    120
## p[372]    150
## p[373]   1200
## p[374]    410
## p[375]   2200
## p[376]   2000
## p[377]   2200
## p[378]    530
## p[379]   2200
## p[380]    140
## p[381]   2200
## p[382]    480
## p[383]   2200
## p[384]    340
## p[385]    930
## p[386]    340
## p[387]    160
## p[388]    420
## p[389]    900
## p[390]    790
## p[391]    840
## p[392]   2200
## p[393]    120
## p[394]   1200
## p[395]    210
## p[396]   1700
## p[397]    710
## p[398]    430
## p[399]    230
## p[400]   2200
## p[401]    370
## p[402]    770
## p[403]    410
## p[404]   2200
## p[405]   2200
## p[406]    190
## p[407]    180
## p[408]   2200
## p[409]    330
## p[410]    470
## p[411]   2200
## p[412]    200
## p[413]   2200
## p[414]   2200
## p[415]   2200
## p[416]    360
## p[417]   2200
## p[418]    290
## p[419]   1000
## p[420]    460
```

```
## p[421]     2200
## p[422]     2200
## p[423]      210
## p[424]     2200
## p[425]     1500
## p[426]      240
## p[427]     2200
## p[428]      110
## p[429]     2200
## p[430]      910
## p[431]     2200
## p[432]     1600
## p[433]     2200
## p[434]     1400
## p[435]     2200
## p[436]      160
## p[437]     2200
## p[438]      380
## p[439]      380
## p[440]     2200
## p[441]      120
## p[442]     2200
## p[443]     2200
## p[444]      270
## p[445]      750
## p[446]      670
## p[447]      140
## p[448]     2200
## p[449]      220
## p[450]      240
## p[451]     2200
## p[452]     2200
## p[453]     1100
## p[454]     2200
## p[455]      490
## p[456]      160
## p[457]     2200
## p[458]      290
## p[459]      730
## p[460]      150
## p[461]     2200
## p[462]      660
## p[463]      140
## p[464]      130
## p[465]      470
## p[466]      180
## p[467]       99
## p[468]     2200
## p[469]      320
## p[470]      120
## p[471]     2200
## p[472]      350
## p[473]      250
## p[474]     2200
```

```
## p[475]     2200
## p[476]     1400
## p[477]     2200
## p[478]     1400
## p[479]      170
## p[480]     1000
## p[481]     1100
## p[482]     2200
## p[483]     2200
## p[484]     2200
## p[485]     1200
## p[486]     2200
## p[487]     2200
## p[488]     2200
## p[489]      250
## p[490]     2100
## p[491]     2200
## p[492]     2200
## p[493]      130
## p[494]     2200
## p[495]     2200
## p[496]     2200
## p[497]     2200
## p[498]      240
## p[499]     2200
## p[500]     2200
## p[501]     2200
## p[502]     2200
## p[503]      230
## p[504]     2200
## p[505]      440
## p[506]     2200
## p[507]      140
## p[508]     2200
## p[509]     1200
## p[510]      100
## p[511]     1600
## p[512]     2200
## p[513]      210
## p[514]      610
## p[515]     2200
## p[516]      470
## p[517]     2200
## p[518]      430
## p[519]     2200
## p[520]     2200
## p[521]     1400
## p[522]      520
## p[523]      150
## p[524]      370
## p[525]      310
## p[526]     1500
## p[527]      490
## p[528]      510
```

```
## p[529]       280
## p[530]       290
## p[531]      2200
## p[532]       180
## p[533]       690
## p[534]       250
## p[535]       270
## p[536]      2100
## p[537]       360
## p[538]       450
## p[539]       250
## p[540]      2200
## p[541]       420
## p[542]      2200
## p[543]      2200
## p[544]      1200
## p[545]      1000
## p[546]       810
## p[547]       280
## p[548]        86
## p[549]       230
## p[550]       350
## p[551]      2200
## p[552]      2200
## p[553]       110
## p[554]      1700
## p[555]       140
## p[556]       900
## p[557]       370
## p[558]       380
## p[559]      2200
## p[560]       270
## p[561]       130
## p[562]      2200
## p[563]       120
## p[564]       380
## p[565]       380
## p[566]      2200
## p[567]       130
## p[568]       350
## p[569]       180
## p[570]       280
## p[571]      2200
## p[572]       210
## p[573]       180
## p[574]       280
## p[575]      2200
## p[576]      1700
## p[577]      2200
## p[578]      2200
## p[579]       120
## p[580]       300
## p[581]      2200
## p[582]       520
```

```
## p[583]     1300
## p[584]     2200
## p[585]     1500
## p[586]      260
## p[587]      970
## p[588]      180
## p[589]      380
## p[590]     1200
## p[591]     2200
## p[592]      170
## p[593]      110
## p[594]      990
## p[595]     2200
## p[596]     2200
## p[597]     2200
## p[598]      950
## p[599]      460
## p[600]      220
## p[601]      450
## p[602]     2200
## p[603]      340
## p[604]     1200
## p[605]     2200
## p[606]      730
## p[607]     2200
## p[608]     1100
## p[609]      190
## p[610]     2200
## p[611]      440
## p[612]      290
## p[613]      670
## p[614]      480
## p[615]      210
## p[616]      610
## p[617]      750
## p[618]     1800
## p[619]      150
## p[620]      490
## p[621]      560
## p[622]     1700
## p[623]     1700
## p[624]     2200
## p[625]     2200
## p[626]      120
## p[627]     1200
## p[628]     2200
## p[629]     2200
## p[630]      730
## p[631]     2200
## p[632]      190
## p[633]       94
## p[634]      260
## p[635]      180
## p[636]      520
```

```
## p[637]     410
## p[638]    1900
## p[639]     220
## p[640]     230
## p[641]     710
## p[642]     280
## p[643]    1900
## p[644]    1200
## p[645]     530
## p[646]     280
## p[647]    2200
## p[648]    1900
## p[649]     810
## p[650]     910
## p[651]     130
## p[652]    2200
## p[653]     130
## p[654]     430
## p[655]    2200
## p[656]    2200
## p[657]     120
## p[658]     400
## p[659]    2200
## p[660]    1400
## p[661]    2100
## p[662]    1100
## p[663]     220
## p[664]     120
## p[665]    1200
## p[666]    2200
## p[667]     270
## p[668]     400
## p[669]    2200
## p[670]     620
## p[671]     490
## p[672]     140
## p[673]    2200
## p[674]    2000
## p[675]     500
## p[676]      97
## p[677]     400
## p[678]    2200
## p[679]     390
## p[680]    2200
## p[681]    2200
## p[682]    2200
## p[683]    2200
## p[684]     300
## p[685]    2200
## p[686]    2200
## p[687]     330
## p[688]     540
## p[689]     250
## p[690]     290
```

```
## p[691]     2200
## p[692]     2200
## p[693]      410
## p[694]     2200
## p[695]     2200
## p[696]      160
## p[697]     1900
## p[698]     2200
## p[699]      330
## p[700]      500
## p[701]      240
## p[702]      330
## p[703]      940
## p[704]     1000
## p[705]      730
## p[706]      180
## p[707]      380
## p[708]      150
## p[709]      250
## p[710]      350
## p[711]     1300
## p[712]     2200
## p[713]     2200
## p[714]      260
## p[715]      840
## p[716]       89
## p[717]      470
## p[718]      300
## p[719]     2200
## p[720]     2200
## p[721]      400
## p[722]     2200
## p[723]     2200
## p[724]     2200
## p[725]      920
## p[726]     2200
## p[727]     1900
## p[728]     2200
## p[729]      390
## p[730]     2000
## p[731]      180
## p[732]     1500
## p[733]     2200
## p[734]      240
## p[735]     1700
## p[736]     2200
## p[737]     1200
## p[738]      140
## p[739]     1200
## p[740]      490
## p[741]       94
## p[742]     2200
## p[743]     2200
## p[744]      570
```

```
## p[745]      120
## p[746]      150
## p[747]      130
## p[748]      130
## p[749]     2200
## p[750]     1300
## p[751]      580
## p[752]      140
## p[753]     1800
## p[754]      460
## p[755]      200
## p[756]      210
## p[757]      120
## p[758]     2200
## p[759]     2200
## p[760]      130
## p[761]      470
## p[762]      120
## p[763]      380
## p[764]      200
## p[765]      630
## p[766]      130
## p[767]      230
## p[768]      390
## p[769]      320
## p[770]     2200
## p[771]      410
## p[772]      390
## p[773]      310
## p[774]      520
## p[775]     2200
## p[776]       89
## p[777]     1400
## p[778]     2200
## p[779]      330
## p[780]      530
## p[781]      210
## p[782]      160
## p[783]      660
## p[784]     2200
## p[785]      110
## p[786]     2200
## p[787]      170
## p[788]      100
## p[789]     2200
## p[790]      200
## p[791]      320
## p[792]      800
## p[793]     2200
## p[794]     2200
## p[795]      250
## p[796]      710
## p[797]      470
## p[798]      570
```

```
## p[799]     1200
## p[800]      410
## p[801]       92
## p[802]     2000
## p[803]      540
## p[804]       99
## p[805]     2200
## p[806]      150
## p[807]     2200
## p[808]     2200
## p[809]     2200
## p[810]      170
## p[811]     1100
## p[812]      600
## p[813]     2200
## p[814]      200
## p[815]     2200
## p[816]      950
## p[817]      510
## deviance  2200
##
## For each parameter, n.eff is a crude measure of effective sample size,
## and Rhat is the potential scale reduction factor (at convergence, Rhat=1).
##
## DIC info (using the rule, pD = var(deviance)/2)
## pD = 6.8 and DIC = 1029.3
## DIC is an estimate of expected predictive error (lower deviance is better).
```

To make a table of Bayesian logit results, you must remember that the printout of results contains also the predicted probabilities for each observation. It is best, therefore, to tell your table making function to only report the parameters that contain the coefficient results. You can do this using the same matrix notation as before, however the difference is that you specify rows as well as columns.

```
#making a table of resutls
regtable<-xtable(pro.fit$BUGSoutput$summary[c("beta1", "beta2",
                "beta3", "beta4", "beta5", "beta6", "beta7", "deviance"),
                c(1,2,3,7)], digits = 4)
print(regtable, type="latex")
```

```
## % latex table generated in R 3.6.3 by xtable 1.8-4 package
## % Mon May 25 15:14:00 2020
## \begin{table}[ht]
## \centering
## \begin{tabular}{rrrrr}
##   \hline
##  & mean & sd & 2.5\% & 97.5\% \\
##   \hline
## beta1 & 3.4198 & 0.5430 & 2.3349 & 4.4867 \\
##   beta2 & 0.0062 & 0.0045 & -0.0025 & 0.0149 \\
##   beta3 & 0.6283 & 0.1605 & 0.3071 & 0.9473 \\
##   beta4 & 0.2165 & 0.2314 & -0.2253 & 0.6731 \\
##   beta5 & -0.0936 & 0.0419 & -0.1757 & -0.0113 \\
##   beta6 & -0.2774 & 0.0965 & -0.4710 & -0.0920 \\
##   beta7 & -0.2438 & 0.0313 & -0.3040 & -0.1805 \\
##   deviance & 1022.4999 & 3.6806 & 1017.3236 & 1031.1276 \\
```

```
##    \hline
## \end{tabular}
## \end{table}
```

```
#converting data to mcmc

logit.mcmc<-as.mcmc(pro.fit)
logit.mat<-as.matrix(logit.mcmc)
logit.out<-as.data.frame(logit.mat)
```

Predicted Probabilities

The actual scale of the logit function has not changed. So, a one unit increase in x leads to a β change in the log odds of y. Therefore, the most appropriate way to present results are using predicted probabilities. The code below demonstrates out of sample predicted probability plots

```
#beta matrix
b<-logit.mat[,1:7]

#Out of sample new data
new.age<-seq(min(age), max(age), length=817)
new.female<-rep(median(female), length(new.age))
new.tumember<-rep(median(tumember), length(tumember))
new.partyid<-rep(median(partyid), length(new.age))
new.schooling<-rep(median(schooling), length(new.age))
new.ideology<-rep(median(ideology), length(new.age))
constant<-rep(1, length(new.age))

tumember<-rep(1, length(new.age))
tunonmember<-rep(0, length(new.age))

#only allowing age to vary
pro.sim<-cbind(constant, new.age, new.female, new.tumember,
               new.partyid, new.schooling, new.ideology)

#new datasets for trade union memebers/non memebers
pro.sim.m<-cbind(constant, new.age, new.female, tumember,
                 new.partyid, new.schooling, new.ideology)

pro.sim.non<-cbind(constant, new.age, new.female, tunonmember,
                   new.partyid, new.schooling, new.ideology)

Xb<-t(pro.sim%*%t(b))

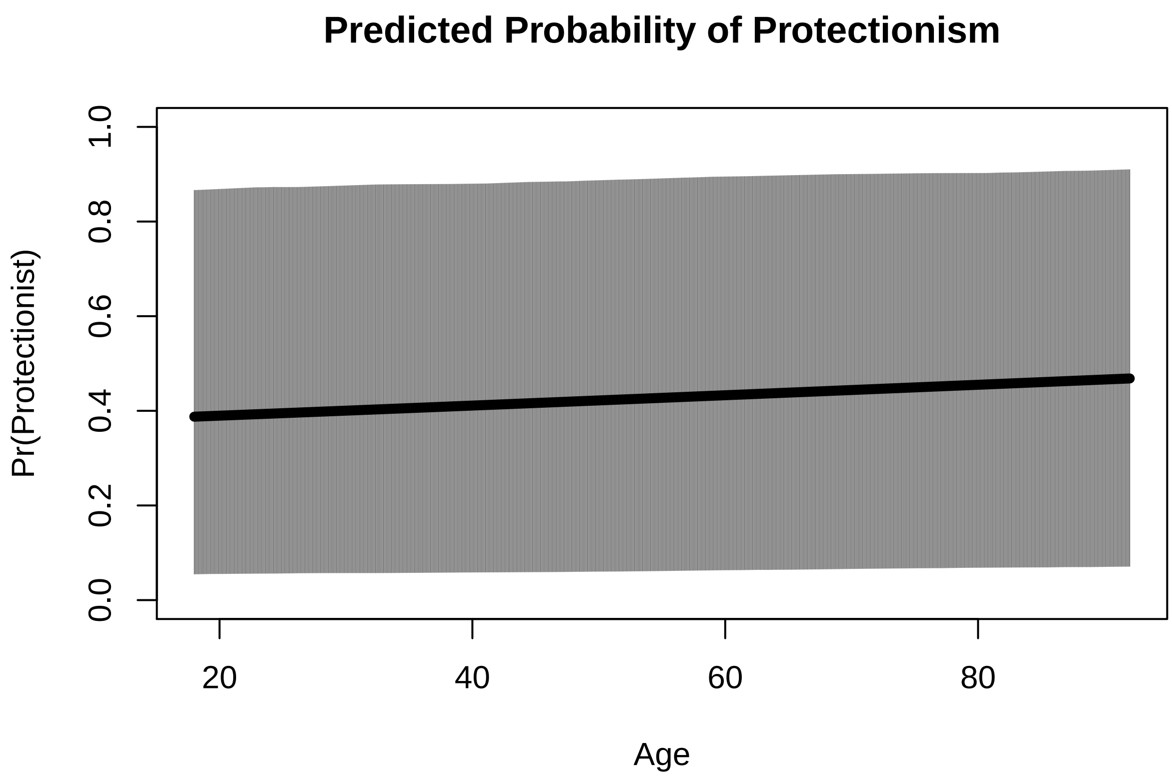
Xb2<-t(pro.sim.m%*%t(b))
Xb3<-t(pro.sim%*%t(b))

pro.pp.age<-exp(Xb)/(1+exp(Xb))

pro.ci.age<-apply(pro.pp.age, 2, quantile, probs=c(0.025, 0.975))

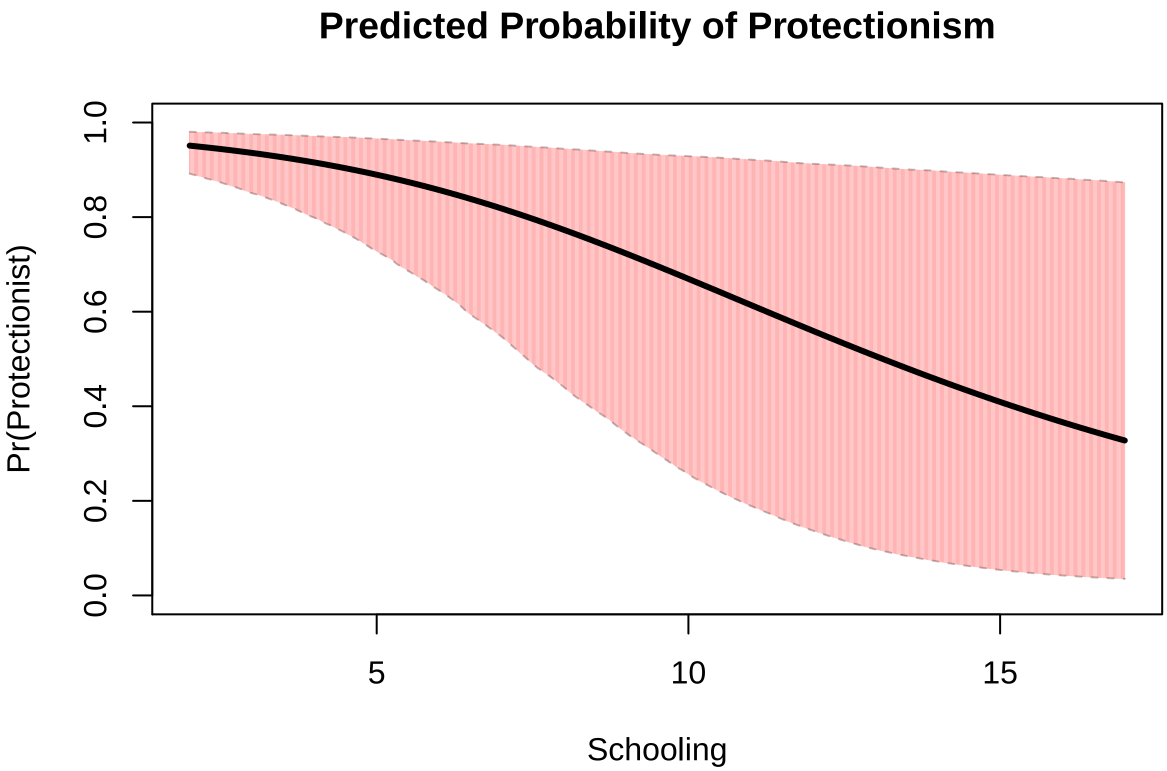
mean.pro.pp.age<-apply(pro.pp.age, 2, mean)
mean.pro.ci.age<-apply(pro.ci.age, 2, quantile, probs=c(.025, .975))
```

```r
plot(new.age, mean.pro.pp.age, lty=1 ,
     main="Predicted Probability of Protectionism",
     xlab="Age", ylab="Pr(Protectionist)", ylim=c(0,1), type="l", lwd=5)

segments(new.age, mean.pro.ci.age[1,], new.age, mean.pro.ci.age[2,], lwd=.1)
```




```r
#The effect of school on protectionism


schooling.sim<-seq(min(schooling), max(schooling), length=817)
new.age1<-rep(median(age), length=817)
new.female<-rep(median(female), length(new.age1))
new.tumember<-rep(median(tumember), length(new.age1) )
new.partyid<-rep(median(partyid), length(new.age1))
new.schooling<-rep(median(schooling), length(new.age1))
new.ideology<-rep(median(ideology), length(new.age1))
constant<-rep(1, length(new.age1))

pro.sim.sch<-cbind(constant, new.age1, new.female, new.tumember,
                   new.partyid, schooling.sim, new.ideology)

Xb.sch<-t(pro.sim.sch%*%t(b))
pro.pp.sch<-exp(Xb.sch)/(1+exp(Xb.sch))
pro.ci.sch<-apply(pro.pp.sch, 2, quantile, probs=c(0.025, 0.975))
mean.pro.pp.sch<-apply(pro.pp.sch, 2, mean)
mean.pro.ci.sch<-apply(pro.ci.sch, 2, quantile, probs=c(.025, .975))

plot(schooling.sim, mean.pro.pp.sch, lty=1 ,
     main="Predicted Probability of Protectionism", xlab="Schooling",
```

```
     ylab="Pr(Protectionist)", ylim=c(0,1), type="l", pch=50)

lines(schooling.sim, mean.pro.ci.sch[1,], lty=2, col="grey")
lines(schooling.sim, mean.pro.ci.sch[2,], lty=2, col="grey")

segments(schooling.sim, mean.pro.ci.sch[1,], schooling.sim,
         mean.pro.ci.sch[2,], col=rgb(1, 0, 0 ,.5), lwd=.3)
lines(schooling.sim, mean.pro.pp.sch, lty=1, lwd=3)
```



Ordered Logit Example

Ordered Logit models are a bit more difficult to estimate than the classic binomial logit. This difference is mainly to do with the nature of the multiple possible outcomes. Coding the model in JAGS require you also consider the cutpoints of the model. The predicted probabilities also become more complicated, as you need to calculated the predicted probability of the observation falling into each category. Below, I have an example of an ordered logit model where the dependent variable is the quality rating of beer brands.

```
#In ordered logit, there is no intercept.  You can either estimate j-1 cutpoints OR estimate intercept

#in Multinomial, we get j-1 sets of regression coefficients, one for each category relative to the omit



library(R2jags)
library(foreign)
library(lattice)
beer<-list( price = c(7.19, 3.15, 3.35, 2.59, 4.59, 4.39, 2.99, 2.49, 3.65, 2.59, 2.89, 2.99, 2.29, 4.7
```

```
price<-beer$price
calories<-beer$calories
sodium<-beer$sodium
alcohol<-beer$alcohol
quality<-beer$quality
N<-length(beer$price)

beer.model.jags<-function(){
    for (i in 1:N){
        for (j in 1:2){
            logit(gamma[i,j]) <- theta1[j] - mu[i]
            }
        quality[i] ~ dcat(p[i,1:3])
        p[i,1]<- gamma[i,1]
        p[i,2] <- gamma[i,2] - gamma[i,1]
        p[i,3] <- 1-gamma[i,2]
        mu[i] <-  b1*price[i] + b2*sodium[i] + b3*alcohol[i]+b4*calories[i] #define linear predictor

        pred[i,1] <- equals(p[i,1], max(p[i,1], p[i,2], p[i,3]))
        pred[i,2] <- equals(p[i,2], max(p[i,1], p[i,2], p[i,3]))
        pred[i,3] <- equals(p[i,3], max(p[i,1], p[i,2], p[i,3]))

        predcat[i] <- pred[i,1] + 2*pred[i,2] + 3*pred[i,3]

        }
        for (k in 1:2) {
            theta[k] ~ dnorm(0, .1) #define cutpoints to be esitmated (always on linear predictor scale
            }
        theta1[1:2] <- sort(theta)
        b1 ~ dnorm(0, .01)
        b2 ~ dnorm(0, .01)
        b3 ~ dnorm(0, .01)
        b4 ~ dnorm(0, .01)

        }


beer.data  <- list("price", "calories", "sodium", "alcohol", "quality", "N")
beer.data<-list(price=price, calories=calories, alcohol=alcohol, quality=quality, sodium=sodium, N=N)


beer.params <- c("b1", "b2", "b3", "b4", "predcat")

beer.inits <- function(){
  list("b1"=c(0.56), "b2"=c(-0.05), "b3"=c(0.95), "b4"=c(0.03), "theta"=c(7,10))
}

beerfit <- jags(data=beer.data, inits=beer.inits, beer.params, n.chains=2, n.iter=2000, n.burnin=500, mo
```

```
## Compiling model graph
##    Resolving undeclared variables
##    Allocating nodes
## Graph information:
##    Observed stochastic nodes: 35
```

```
##    Unobserved stochastic nodes: 6
##    Total graph size: 795
##
## Initializing model
```

```r
beerfit<- autojags(beerfit)

print(beerfit)
```

```
## Inference for Bugs model at "/var/folders/dx/pkx9cyj1089843ljm_jzj3pm0000gn/T//RtmpGm3cAX/model3fc51
##  2 chains, each with 1000 iterations (first 0 discarded)
##  n.sims = 2000 iterations saved
##              mu.vect sd.vect   2.5%    25%    50%    75%  97.5%  Rhat n.eff
## b1             0.456   0.339 -0.179  0.231  0.430  0.658  1.185 1.006   290
## b2            -0.079   0.059 -0.198 -0.117 -0.080 -0.041  0.041 1.053    36
## b3            -1.295   1.004 -2.760 -2.130 -1.548 -0.467  0.809 3.677     2
## b4             0.061   0.033 -0.013  0.036  0.065  0.089  0.107 3.563     3
## predcat[1]     2.897   0.333  2.000  3.000  3.000  3.000  3.000 1.089   130
## predcat[2]     1.968   0.420  1.000  2.000  2.000  2.000  3.000 1.094    24
## predcat[3]     2.169   0.441  1.000  2.000  2.000  2.000  3.000 1.041    55
## predcat[4]     2.018   0.376  1.000  2.000  2.000  2.000  3.000 1.022  2000
## predcat[5]     2.805   0.396  2.000  3.000  3.000  3.000  3.000 1.050    56
## predcat[6]     2.977   0.150  3.000  3.000  3.000  3.000  3.000 1.278    52
## predcat[7]     2.779   0.431  2.000  3.000  3.000  3.000  3.000 1.193    17
## predcat[8]     2.068   0.416  1.000  2.000  2.000  2.000  3.000 1.078    35
## predcat[9]     2.841   0.371  2.000  3.000  3.000  3.000  3.000 1.092    42
## predcat[10]    1.941   0.412  1.000  2.000  2.000  2.000  3.000 1.005  2000
## predcat[11]    2.414   0.519  2.000  2.000  2.000  3.000  3.000 1.105    20
## predcat[12]    2.374   0.510  2.000  2.000  2.000  3.000  3.000 1.156    14
## predcat[13]    2.411   0.576  1.000  2.000  2.000  3.000  3.000 1.061    54
## predcat[14]    2.861   0.352  2.000  3.000  3.000  3.000  3.000 1.049    71
## predcat[15]    1.526   0.528  1.000  1.000  2.000  2.000  2.000 1.023    72
## predcat[16]    1.210   0.463  1.000  1.000  1.000  1.000  2.000 1.663     6
## predcat[17]    2.728   0.450  2.000  2.000  3.000  3.000  3.000 1.050    50
## predcat[18]    2.010   0.458  1.000  2.000  2.000  2.000  3.000 1.050    99
## predcat[19]    1.192   0.419  1.000  1.000  1.000  1.000  2.000 1.602     6
## predcat[20]    2.288   0.618  1.000  2.000  2.000  3.000  3.000 1.074    36
## predcat[21]    1.866   0.405  1.000  2.000  2.000  2.000  2.000 1.003   630
## predcat[22]    2.064   0.555  1.000  2.000  2.000  2.000  3.000 1.027   110
## predcat[23]    1.625   0.575  1.000  1.000  2.000  2.000  3.000 1.005   310
## predcat[24]    2.576   0.510  2.000  2.000  3.000  3.000  3.000 1.010   590
## predcat[25]    1.905   0.600  1.000  2.000  2.000  2.000  3.000 1.125    19
## predcat[26]    1.978   0.499  1.000  2.000  2.000  2.000  3.000 1.062    47
## predcat[27]    1.815   0.513  1.000  2.000  2.000  2.000  3.000 1.146    17
## predcat[28]    1.318   0.548  1.000  1.000  1.000  2.000  3.000 1.846     4
## predcat[29]    1.347   0.529  1.000  1.000  1.000  2.000  3.000 1.250    11
## predcat[30]    2.277   0.505  1.000  2.000  2.000  3.000  3.000 1.028   110
## predcat[31]    1.811   0.444  1.000  2.000  2.000  2.000  2.000 1.008   300
## predcat[32]    2.233   0.573  1.000  2.000  2.000  3.000  3.000 1.034   190
## predcat[33]    2.303   0.575  1.000  2.000  2.000  3.000  3.000 1.018   110
## predcat[34]    1.452   0.528  1.000  1.000  1.000  2.000  2.000 1.115    18
## predcat[35]    1.220   0.434  1.000  1.000  1.000  1.000  2.000 1.033    91
## deviance      71.568   3.407 66.120 69.238 71.131 73.406 79.713 1.029    92
##
## For each parameter, n.eff is a crude measure of effective sample size,
```

```
## and Rhat is the potential scale reduction factor (at convergence, Rhat=1).
##
## DIC info (using the rule, pD = var(deviance)/2)
## pD = 5.7 and DIC = 77.3
## DIC is an estimate of expected predictive error (lower deviance is better).
```

```r
beer.mcmc <- as.mcmc(beerfit)
summary(beer.mcmc)
```

```
##
## Iterations = 1:1000
## Thinning interval = 1
## Number of chains = 2
## Sample size per chain = 1000
##
## 1. Empirical mean and standard deviation for each variable,
##    plus standard error of the mean:
##
##                  Mean      SD  Naive SE Time-series SE
## b1            0.45604 0.33916 0.0075839       0.036735
## b2           -0.07898 0.05896 0.0013185       0.005798
## b3           -1.29534 1.00382 0.0224461       0.178106
## b4            0.06092 0.03277 0.0007329       0.006039
## deviance     71.56752 3.40717 0.0761866       0.338921
## predcat[1]    2.89650 0.33293 0.0074446       0.023793
## predcat[10]   1.94100 0.41183 0.0092088       0.011642
## predcat[11]   2.41350 0.51928 0.0116115       0.020073
## predcat[12]   2.37450 0.51027 0.0114101       0.021017
## predcat[13]   2.41100 0.57554 0.0128694       0.048031
## predcat[14]   2.86100 0.35177 0.0078658       0.017646
## predcat[15]   1.52550 0.52772 0.0118002       0.022164
## predcat[16]   1.21000 0.46261 0.0103442       0.075981
## predcat[17]   2.72800 0.44957 0.0100528       0.018880
## predcat[18]   2.01000 0.45826 0.0102471       0.032798
## predcat[19]   1.19200 0.41860 0.0093601       0.056553
## predcat[2]    1.96750 0.42016 0.0093950       0.014938
## predcat[20]   2.28850 0.61762 0.0138105       0.055782
## predcat[21]   1.86650 0.40467 0.0090487       0.009687
## predcat[22]   2.06450 0.55542 0.0124196       0.030007
## predcat[23]   1.62500 0.57493 0.0128557       0.031513
## predcat[24]   2.57600 0.51025 0.0114095       0.040029
## predcat[25]   1.90500 0.60013 0.0134193       0.035161
## predcat[26]   1.97850 0.49916 0.0111616       0.030777
## predcat[27]   1.81550 0.51341 0.0114802       0.024041
## predcat[28]   1.31800 0.54775 0.0122480       0.054578
## predcat[29]   1.34700 0.52890 0.0118265       0.045496
## predcat[3]    2.16900 0.44106 0.0098625       0.013255
## predcat[30]   2.27700 0.50537 0.0113004       0.027521
## predcat[31]   1.81100 0.44427 0.0099342       0.012101
## predcat[32]   2.23300 0.57348 0.0128233       0.043466
## predcat[33]   2.30250 0.57459 0.0128483       0.045035
## predcat[34]   1.45150 0.52800 0.0118065       0.022473
## predcat[35]   1.21950 0.43407 0.0097060       0.047988
## predcat[4]    2.01850 0.37580 0.0084032       0.011800
## predcat[5]    2.80550 0.39591 0.0088529       0.016143
```

```
## predcat[6]   2.97700 0.14994 0.0033528       0.005326
## predcat[7]   2.77850 0.43073 0.0096315       0.025926
## predcat[8]   2.06850 0.41581 0.0092977       0.012427
## predcat[9]   2.84150 0.37074 0.0082899       0.016970
##
## 2. Quantiles for each variable:
##
##                 2.5%      25%      50%      75%    97.5%
## b1           -0.17866  0.23139  0.42988  0.65840  1.18523
## b2           -0.19797 -0.11692 -0.07961 -0.04057  0.04119
## b3           -2.76048 -2.12977 -1.54823 -0.46674  0.80896
## b4           -0.01345  0.03642  0.06549  0.08927  0.10696
## deviance     66.12022 69.23848 71.13056 73.40636 79.71254
## predcat[1]    2.00000  3.00000  3.00000  3.00000  3.00000
## predcat[10]   1.00000  2.00000  2.00000  2.00000  3.00000
## predcat[11]   2.00000  2.00000  2.00000  3.00000  3.00000
## predcat[12]   2.00000  2.00000  2.00000  3.00000  3.00000
## predcat[13]   1.00000  2.00000  2.00000  3.00000  3.00000
## predcat[14]   2.00000  3.00000  3.00000  3.00000  3.00000
## predcat[15]   1.00000  1.00000  2.00000  2.00000  2.00000
## predcat[16]   1.00000  1.00000  1.00000  1.00000  2.00000
## predcat[17]   2.00000  2.00000  3.00000  3.00000  3.00000
## predcat[18]   1.00000  2.00000  2.00000  2.00000  3.00000
## predcat[19]   1.00000  1.00000  1.00000  1.00000  2.00000
## predcat[2]    1.00000  2.00000  2.00000  2.00000  3.00000
## predcat[20]   1.00000  2.00000  2.00000  3.00000  3.00000
## predcat[21]   1.00000  2.00000  2.00000  2.00000  2.00000
## predcat[22]   1.00000  2.00000  2.00000  2.00000  3.00000
## predcat[23]   1.00000  1.00000  2.00000  2.00000  3.00000
## predcat[24]   2.00000  2.00000  3.00000  3.00000  3.00000
## predcat[25]   1.00000  2.00000  2.00000  2.00000  3.00000
## predcat[26]   1.00000  2.00000  2.00000  2.00000  3.00000
## predcat[27]   1.00000  2.00000  2.00000  2.00000  3.00000
## predcat[28]   1.00000  1.00000  1.00000  2.00000  3.00000
## predcat[29]   1.00000  1.00000  1.00000  2.00000  3.00000
## predcat[3]    1.00000  2.00000  2.00000  2.00000  3.00000
## predcat[30]   1.00000  2.00000  2.00000  3.00000  3.00000
## predcat[31]   1.00000  2.00000  2.00000  2.00000  2.00000
## predcat[32]   1.00000  2.00000  2.00000  3.00000  3.00000
## predcat[33]   1.00000  2.00000  2.00000  3.00000  3.00000
## predcat[34]   1.00000  1.00000  1.00000  2.00000  2.00000
## predcat[35]   1.00000  1.00000  1.00000  1.00000  2.00000
## predcat[4]    1.00000  2.00000  2.00000  2.00000  3.00000
## predcat[5]    2.00000  3.00000  3.00000  3.00000  3.00000
## predcat[6]    3.00000  3.00000  3.00000  3.00000  3.00000
## predcat[7]    2.00000  3.00000  3.00000  3.00000  3.00000
## predcat[8]    1.00000  2.00000  2.00000  2.00000  3.00000
## predcat[9]    2.00000  3.00000  3.00000  3.00000  3.00000
```

```
chains <- do.call(rbind, beer.mcmc)
pc <- chains[ ,grep("predcat", colnames(chains))]
tab <- apply(pc, 2, function(x)table(factor(x, levels=1:3)))
tab <- t(tab)
library(car)
```

```
## Loading required package: carData
```

```r
prop.table(tab, 1)
```

```
##                  1      2      3
## predcat[1]  0.0090 0.0855 0.9055
## predcat[10] 0.1160 0.8270 0.0570
## predcat[11] 0.0135 0.5595 0.4270
## predcat[12] 0.0130 0.5995 0.3875
## predcat[13] 0.0445 0.5000 0.4555
## predcat[14] 0.0020 0.1350 0.8630
## predcat[15] 0.4890 0.4965 0.0145
## predcat[16] 0.8140 0.1620 0.0240
## predcat[17] 0.0020 0.2680 0.7300
## predcat[18] 0.1000 0.7900 0.1100
## predcat[19] 0.8180 0.1720 0.0100
## predcat[2]  0.1050 0.8225 0.0725
## predcat[20] 0.0880 0.5355 0.3765
## predcat[21] 0.1575 0.8185 0.0240
## predcat[22] 0.1240 0.6875 0.1885
## predcat[23] 0.4230 0.5290 0.0480
## predcat[24] 0.0080 0.4080 0.5840
## predcat[25] 0.2320 0.6310 0.1370
## predcat[26] 0.1355 0.7505 0.1140
## predcat[27] 0.2410 0.7025 0.0565
## predcat[28] 0.7235 0.2350 0.0415
## predcat[29] 0.6795 0.2940 0.0265
## predcat[3]  0.0270 0.7770 0.1960
## predcat[30] 0.0275 0.6680 0.3045
## predcat[31] 0.2110 0.7670 0.0220
## predcat[32] 0.0750 0.6170 0.3080
## predcat[33] 0.0595 0.5785 0.3620
## predcat[34] 0.5640 0.4205 0.0155
## predcat[35] 0.7890 0.2025 0.0085
## predcat[4]  0.0615 0.8585 0.0800
## predcat[5]  0.0000 0.1945 0.8055
## predcat[6]  0.0000 0.0230 0.9770
## predcat[7]  0.0065 0.2085 0.7850
## predcat[8]  0.0545 0.8225 0.1230
## predcat[9]  0.0020 0.1545 0.8435
```

Multilevel Models

The following is an example from Gelman and Hill's book *Data Analysis Using Regression and Multilevel/Hierarchical Models*. The data can be found on Gelman's website: http://www.stat.columbia.edu/~gelman/arm/software/.

When writing multilevel models (hereafter MLM) in JAGs is the biggest difference between MLMs and other models. It is important to keep your indices straight, especially for nested models. With a Bayesian MLM, you can easily create a random intercept or random coefficient by group or individual. How you structure your model will determine which you have. The following model demonstrates how to estimate a random intercept model.

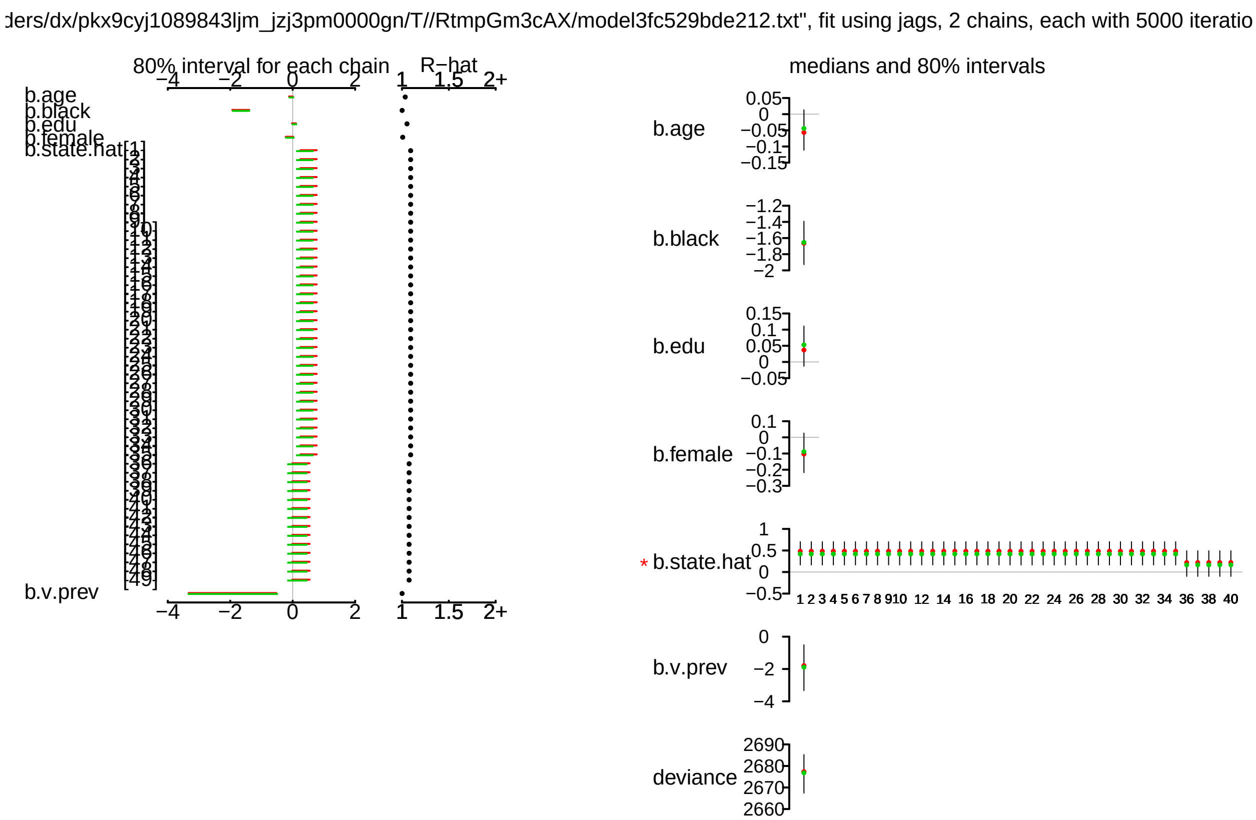
This model is modelling vote choice in the 1988 election. The individual level predictors are age, gender, race, and education. In this model, there is also a random intercept by state, which is based off the previous presidential vote of that state ('p.vote').

```
state.mod <- function() {
  for (i in 1:n){
    y[i] ~ dbin (p.bound[i], 1)
    p.bound[i] <- max(0, min(1, p[i]))
    logit(p[i]) <- Xbeta[i]
    Xbeta[i] <- b.female*female[i] + b.black*black[i] +
      b.age*age[i] + b.edu*edu[i]
      + b.state[state[i]]
  }
  b.female ~ dnorm (0, .01)
  b.black ~ dnorm (0, .01)
  b.age ~ dnorm (0, .01)
  b.edu ~ dnorm (0, .01)


  for (j in 1:n.state){
    b.state[j] ~ dnorm(b.state.hat[j], tau.state)
    b.state.hat[j] <- b.state0 + b.v.prev*v.prev[j]
    }
    b.state.hat.mu<-mean(b.state.hat[])
    b.v.prev ~ dnorm(0, .01)
    b.state0 ~ dnorm(0, .01)
    tau.state <- pow(sigma.state, -2)
    sigma.state ~ dunif (0, 100)
}

library(R2jags)
library(foreign)

#Getting differences in voting data


polls.subset <- read.table("polls.subset.dat")

#previous vote data
pres<-read.dta("presvote.dta")


#merging data

polls.subset.merged<-merge(x=polls.subset, y=pres, by.x = "state", by.y = "stnum2", all.x = TRUE)


y <- polls.subset.merged$bush
female <- polls.subset.merged$female
black <- polls.subset.merged$black
age <- polls.subset.merged$age
edu <- polls.subset.merged$edu
v.prev <- polls.subset.merged$g76_84pr

uniqstate <- unique(polls.subset$state)
polls.subset$stateid <- match(polls.subset$state, uniqstate)
```

```r
state <- polls.subset$stateid



n <- length(y)             # of survey respondents
n.state <- max(state)      # of states


state.dat <- list ("n", "n.state", "y", "female", "black", "age", "edu",
                   "state", "v.prev")

state.params <- c ("b.female", "b.black", "b.age", "b.edu", "b.state.hat",
                   "b.v.prev")

state.inits <- function (){
 list(b.female = c(0), b.black = c(0),
  b.age = c(0), b.edu = c(0), b.state = rnorm(n.state), b.v.prev = c(0))
}

state.fit <- jags(data=state.dat, inits=state.inits, state.params,
                  model.file=state.mod, n.chains=2, n.iter=5000, n.burnin=100)
```

```
## Compiling model graph
##    Resolving undeclared variables
##    Allocating nodes
## Graph information:
##    Observed stochastic nodes: 2015
##    Unobserved stochastic nodes: 234
##    Total graph size: 19326
##
## Initializing model
```

```r
plot(state.fit)
```




```r
print(state.fit)
```

```
## Inference for Bugs model at "/var/folders/dx/pkx9cyj1089843ljm_jzj3pm0000gn/T//RtmpGm3cAX/model3fc52
##  2 chains, each with 5000 iterations (first 100 discarded), n.thin = 4
##  n.sims = 2450 iterations saved
##                    mu.vect sd.vect    2.5%     25%     50%     75%   97.5%
## b.age               -0.050   0.049  -0.142  -0.084  -0.050  -0.019   0.050
## b.black             -1.659   0.209  -2.064  -1.798  -1.658  -1.513  -1.261
## b.edu                0.047   0.048  -0.041   0.014   0.046   0.080   0.145
## b.female            -0.096   0.094  -0.275  -0.160  -0.096  -0.034   0.089
## b.state.hat[1]       0.444   0.203   0.046   0.310   0.451   0.588   0.828
## b.state.hat[2]       0.444   0.203   0.046   0.310   0.451   0.588   0.828
## b.state.hat[3]       0.444   0.203   0.046   0.310   0.451   0.588   0.828
## b.state.hat[4]       0.444   0.203   0.046   0.310   0.451   0.588   0.828
## b.state.hat[5]       0.444   0.203   0.046   0.310   0.451   0.588   0.828
## b.state.hat[6]       0.444   0.203   0.046   0.310   0.451   0.588   0.828
## b.state.hat[7]       0.444   0.203   0.046   0.310   0.451   0.588   0.828
## b.state.hat[8]       0.444   0.203   0.046   0.310   0.451   0.588   0.828
## b.state.hat[9]       0.444   0.203   0.046   0.310   0.451   0.588   0.828
## b.state.hat[10]      0.444   0.203   0.046   0.310   0.451   0.588   0.828
## b.state.hat[11]      0.444   0.203   0.046   0.310   0.451   0.588   0.828
## b.state.hat[12]      0.444   0.203   0.046   0.310   0.451   0.588   0.828
## b.state.hat[13]      0.444   0.203   0.046   0.310   0.451   0.588   0.828
## b.state.hat[14]      0.444   0.203   0.046   0.310   0.451   0.588   0.828
## b.state.hat[15]      0.444   0.203   0.046   0.310   0.451   0.588   0.828
## b.state.hat[16]      0.444   0.203   0.046   0.310   0.451   0.588   0.828
## b.state.hat[17]      0.444   0.203   0.046   0.310   0.451   0.588   0.828
## b.state.hat[18]      0.444   0.203   0.046   0.310   0.451   0.588   0.828
```

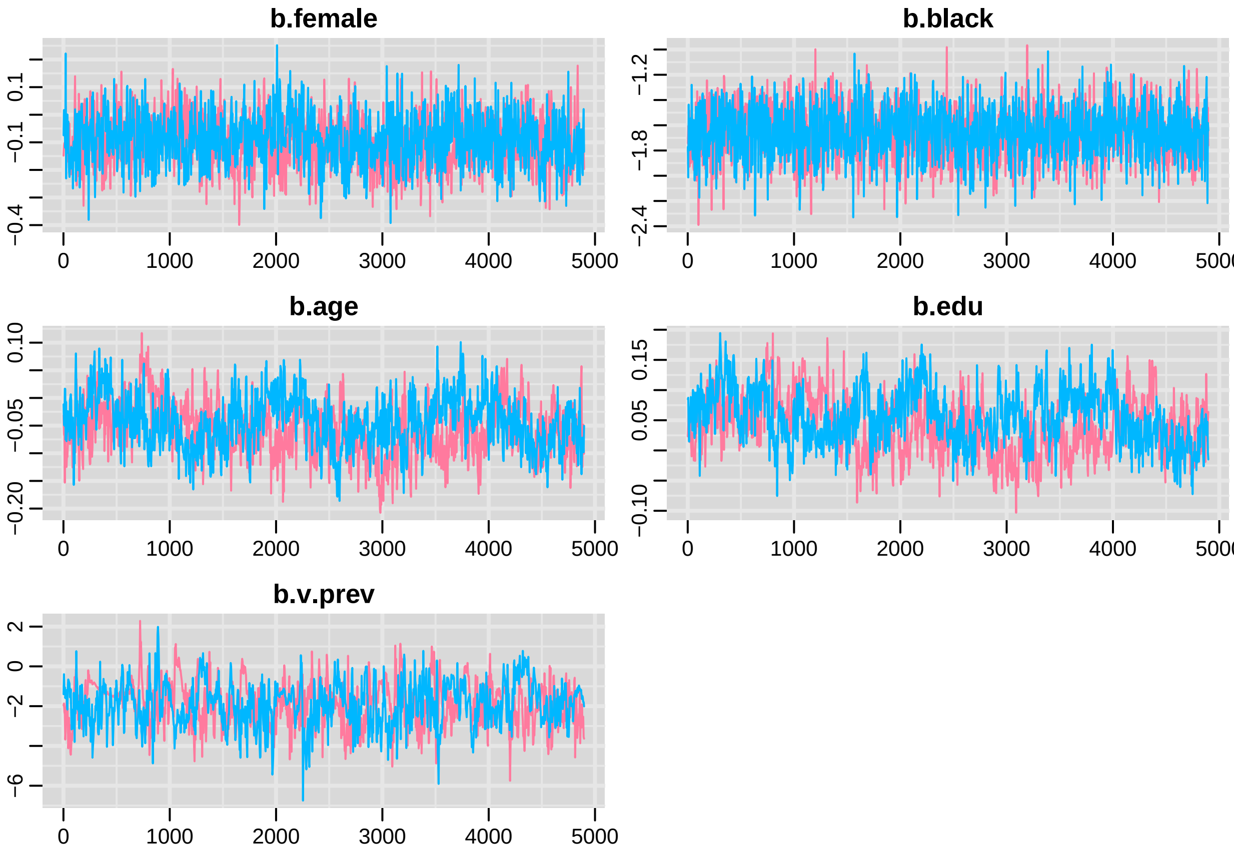
```
## b.state.hat[19]    0.444   0.203    0.046    0.310    0.451    0.588    0.828
## b.state.hat[20]    0.444   0.203    0.046    0.310    0.451    0.588    0.828
## b.state.hat[21]    0.444   0.203    0.046    0.310    0.451    0.588    0.828
## b.state.hat[22]    0.444   0.203    0.046    0.310    0.451    0.588    0.828
## b.state.hat[23]    0.444   0.203    0.046    0.310    0.451    0.588    0.828
## b.state.hat[24]    0.444   0.203    0.046    0.310    0.451    0.588    0.828
## b.state.hat[25]    0.444   0.203    0.046    0.310    0.451    0.588    0.828
## b.state.hat[26]    0.444   0.203    0.046    0.310    0.451    0.588    0.828
## b.state.hat[27]    0.444   0.203    0.046    0.310    0.451    0.588    0.828
## b.state.hat[28]    0.444   0.203    0.046    0.310    0.451    0.588    0.828
## b.state.hat[29]    0.444   0.203    0.046    0.310    0.451    0.588    0.828
## b.state.hat[30]    0.444   0.203    0.046    0.310    0.451    0.588    0.828
## b.state.hat[31]    0.444   0.203    0.046    0.310    0.451    0.588    0.828
## b.state.hat[32]    0.444   0.203    0.046    0.310    0.451    0.588    0.828
## b.state.hat[33]    0.444   0.203    0.046    0.310    0.451    0.588    0.828
## b.state.hat[34]    0.444   0.203    0.046    0.310    0.451    0.588    0.828
## b.state.hat[35]    0.444   0.203    0.046    0.310    0.451    0.588    0.828
## b.state.hat[36]    0.199   0.232   -0.267    0.042    0.200    0.362    0.640
## b.state.hat[37]    0.199   0.232   -0.267    0.042    0.200    0.362    0.640
## b.state.hat[38]    0.199   0.232   -0.267    0.042    0.200    0.362    0.640
## b.state.hat[39]    0.199   0.232   -0.267    0.042    0.200    0.362    0.640
## b.state.hat[40]    0.199   0.232   -0.267    0.042    0.200    0.362    0.640
## b.state.hat[41]    0.199   0.232   -0.267    0.042    0.200    0.362    0.640
## b.state.hat[42]    0.199   0.232   -0.267    0.042    0.200    0.362    0.640
## b.state.hat[43]    0.199   0.232   -0.267    0.042    0.200    0.362    0.640
## b.state.hat[44]    0.199   0.232   -0.267    0.042    0.200    0.362    0.640
## b.state.hat[45]    0.199   0.232   -0.267    0.042    0.200    0.362    0.640
## b.state.hat[46]    0.199   0.232   -0.267    0.042    0.200    0.362    0.640
## b.state.hat[47]    0.199   0.232   -0.267    0.042    0.200    0.362    0.640
## b.state.hat[48]    0.199   0.232   -0.267    0.042    0.200    0.362    0.640
## b.state.hat[49]    0.199   0.232   -0.267    0.042    0.200    0.362    0.640
## b.v.prev          -1.900   1.106   -4.067   -2.654   -1.832   -1.172    0.214
## deviance        2676.679   7.000 2662.302 2671.876 2677.127 2681.444 2689.650
##                  Rhat n.eff
## b.age           1.035    49
## b.black         1.001  2200
## b.edu           1.054    34
## b.female        1.008   210
## b.state.hat[1]  1.092    22
## b.state.hat[2]  1.092    22
## b.state.hat[3]  1.092    22
## b.state.hat[4]  1.092    22
## b.state.hat[5]  1.092    22
## b.state.hat[6]  1.092    22
## b.state.hat[7]  1.092    22
## b.state.hat[8]  1.092    22
## b.state.hat[9]  1.092    22
## b.state.hat[10] 1.092    22
## b.state.hat[11] 1.092    22
## b.state.hat[12] 1.092    22
## b.state.hat[13] 1.092    22
## b.state.hat[14] 1.092    22
## b.state.hat[15] 1.092    22
## b.state.hat[16] 1.092    22
```

```
## b.state.hat[17] 1.092    22
## b.state.hat[18] 1.092    22
## b.state.hat[19] 1.092    22
## b.state.hat[20] 1.092    22
## b.state.hat[21] 1.092    22
## b.state.hat[22] 1.092    22
## b.state.hat[23] 1.092    22
## b.state.hat[24] 1.092    22
## b.state.hat[25] 1.092    22
## b.state.hat[26] 1.092    22
## b.state.hat[27] 1.092    22
## b.state.hat[28] 1.092    22
## b.state.hat[29] 1.092    22
## b.state.hat[30] 1.092    22
## b.state.hat[31] 1.092    22
## b.state.hat[32] 1.092    22
## b.state.hat[33] 1.092    22
## b.state.hat[34] 1.092    22
## b.state.hat[35] 1.092    22
## b.state.hat[36] 1.076    25
## b.state.hat[37] 1.076    25
## b.state.hat[38] 1.076    25
## b.state.hat[39] 1.076    25
## b.state.hat[40] 1.076    25
## b.state.hat[41] 1.076    25
## b.state.hat[42] 1.076    25
## b.state.hat[43] 1.076    25
## b.state.hat[44] 1.076    25
## b.state.hat[45] 1.076    25
## b.state.hat[46] 1.076    25
## b.state.hat[47] 1.076    25
## b.state.hat[48] 1.076    25
## b.state.hat[49] 1.076    25
## b.v.prev        1.001  2400
## deviance        1.004   460
##
## For each parameter, n.eff is a crude measure of effective sample size,
## and Rhat is the potential scale reduction factor (at convergence, Rhat=1).
##
## DIC info (using the rule, pD = var(deviance)/2)
## pD = 24.5 and DIC = 2701.1
## DIC is an estimate of expected predictive error (lower deviance is better).
```

```
state.mcmc<-as.mcmc(state.fit)

library(mcmcplots)
```

```
## Registered S3 method overwritten by 'mcmcplots':
##   method        from
##   as.mcmc.rjags R2jags
```

```
traplot(state.fit, parms = c("b.female", "b.black", "b.age", "b.edu", "b.v.prev"))
```



Random Coefficient Model

The above example demonstrates a random intercept by group. However, it is also possible to include a random slope. To do this, you need to include a *hyperprior*, or a prior on a prior. Below is an example. Notice that the mu is defined with the parameters alpha and alpha2. However, those two parameters are also indexed by individual (i) and have priors of their own. This allows for each individual to have their own slope parameter in the model.

```
model<-function(){
 for(i in 1:9249)
  {
   for(t in 1:2)
    {
     y[i,t]~dnorm(mu[i,t],sigma2inv)
     mu[i,t]<-alpha[i]+alpha1*x1[i]+alpha2[i]*x2[i,t]
    }
 alpha[i]~dnorm(alpha0,tau2inv)
 alpha2[i]~dnorm(alpha20,tau20inv)
  }
 alpha0~dnorm(0,1.0E-4)
 alpha1~dnorm(0,1.0E-4)
 alpha20~dnorm(0,1.0E-4)

 sigma2inv~dgamma(.1,.1)
 sigma2<-1/sqrt(sigma2inv)
```

```
 tau2inv~dgamma(.01,.01)
 tau2<-1/sqrt(tau2inv)

 tau20inv~dgamma(.1,.1)
 tau20<-1/sqrt(tau20inv)

}
```

Naive Bayes Classification

Here, I am using a movie review corpus, which can be downloaded from the internet. Text analysis in R requires many libraries. Therefore, to help load the libraries quickly, I use the `pacman` command.

```
#install.packages("pacman")
library(pacman)
pacman::p_load(tm, SnowballC, foreign, plyr, twitteR, slam, foreign,
               wordcloud, LiblineaR, e1071, quanteda)
```

Cleaning Text

The most time intensive part of text analysis is cleaning the text. This means taking out numbers, punctuation, capitalization, special characters, etc. The goal is to get a corpus of plain text. The text cleaner also gets rid of "stop words", which are simply words like "and", "or", "the", "a", "and" that do not contribute substantively to the text, and therefore do not contribute to the model.

The code below creates a function called `text_cleaner` and runs that function over the corpus of movie reviews. Once the movie reviews are clean, you can create a document term matrix. This is a matrix where the rows are the documents and the columns are the words. Each cell represents the frequency of that word in that document.

```
#Data
reviews<-read.csv("https://www.ocf.berkeley.edu/~janastas/data/movie-pang02.csv")

#1. Clean text

text_cleaner<-function(corpus, rawtext){
  tempcorpus = lapply(corpus,toString)
  for(i in 1:length(tempcorpus)){
    tempcorpus[[i]]<-iconv(tempcorpus[[i]], "ASCII", "UTF-8", sub="")
  }
  if(rawtext == TRUE){
    tempcorpus = lapply(tempcorpus, function(t) t$getText())
  }
  tempcorpus = lapply(tempcorpus, tolower)
  tempcorpus<-Corpus(VectorSource(tempcorpus))
  tempcorpus<-tm_map(tempcorpus,
                     removePunctuation)
  tempcorpus<-tm_map(tempcorpus,
                     removeNumbers)
  tempcorpus<-tm_map(tempcorpus,
                     removeWords, stopwords("english"))
  tempcorpus<-tm_map(tempcorpus,
                     stemDocument)
```

```r
  tempcorpus<-tm_map(tempcorpus,
                     stripWhitespace)
  return(tempcorpus)
}

review_text<-reviews$text

clean_reviews<-text_cleaner(review_text, rawtext=FALSE)
```

```
## Warning in tm_map.SimpleCorpus(tempcorpus, removePunctuation): transformation
## drops documents

## Warning in tm_map.SimpleCorpus(tempcorpus, removeNumbers): transformation drops
## documents

## Warning in tm_map.SimpleCorpus(tempcorpus, removeWords, stopwords("english")):
## transformation drops documents

## Warning in tm_map.SimpleCorpus(tempcorpus, stemDocument): transformation drops
## documents

## Warning in tm_map.SimpleCorpus(tempcorpus, stripWhitespace): transformation
## drops documents
```

```r
#Document Term Matrix
dtm<-DocumentTermMatrix(clean_reviews)
dtm=removeSparseTerms(dtm, .99)
inspect(dtm[1:5,1:5])
```

```
## <<DocumentTermMatrix (documents: 5, terms: 5)>>
## Non-/sparse entries: 9/16
## Sparsity           : 64%
## Maximal term length: 6
## Weighting          : term frequency (tf)
## Sample             :
##     Terms
## Docs accent act actual adapt alan
##    1      2   2      1     1    1
##    2      0   0      0     0    0
##    3      0   1      1     0    0
##    4      0   6      4     0    0
##    5      0   0      0     0    0
```

Training the Model

Before we can classify reviews, we first need to separate our data into training and test set. The code below shows how to assign observations randomly into a test and training set. Once you have a training set, you can train the model by using the `naiveBayes` command. "Training" a model in machine learning means to teach your model to distinguish between "positive" and "negative" reviews. You feed the model reviews and tell it if that review was positive or negative and the then the algorithm finds which words are more common in each type of review.

```r
#Making the DV (Sentiment) numeric
positive<-ifelse(reviews$class=="Pos", 1, 0)
```

```r
#Split sample

#take a sample of the reviews and mark 85% of them for training
train=sample(1:dim(reviews)[1], dim(reviews)[1]*0.85)

#turn DTM into plain matrix to help
dtm_mat<-as.matrix(dtm)

#Gather only the rows of the DTM and rating (pos reviews) that are marked for training
trainX=dtm_mat[train]
trainY=positive[train]

#Gather everything that isn't marked for training
testX=dtm_mat[-train]
testY=positive[-train]

#Turn the test/train set back into a DTM
dtmtrainX<-as.data.frame(trainX)
dtmtrainX<-Corpus(VectorSource(dtmtrainX))
dtmtrainX<-DocumentTermMatrix(dtmtrainX)

dtmtestX<-as.data.frame(testX)
dtmtestX<-Corpus(VectorSource(dtmtestX))
dtmtestX<-DocumentTermMatrix(dtmtestX)

#Include only frequently used words (helps speed things up)
ten_words<-findFreqTerms(dtmtrainX, 10)
ten_words[(length(ten_words)-20):length(ten_words)]
```

```
## character(0)
```

```r
#New objects that are teh DTM for only the most frequent words
fword_train<-DocumentTermMatrix(clean_reviews[train])
fword_test<-DocumentTermMatrix(clean_reviews[-train])

#Counts, how many times does this work appear in this rating (pos or neg)
counts<-function(x){
    y<-ifelse(x>0, 1,0)
    y<-factor(y, levels=c(0,1))
    y
}

fword_train<-apply(fword_train, 2, counts)
fword_test<-apply(fword_test, 2, counts)


#Training the Model
trainedNBclassifier<-naiveBayes(x=fword_train, y=factor(trainY))
```

Testing and Evaluating the Model

Your training model provides you will coefficients for lack of a better term. The training model is looking for statistical relationships between the frequency of certain words and the positive movie reviews. We can then let the model run on the test set to see if we can predict the movie review categories. We test our model with the simple `predict` command. After we test our model, we evaluate our model with the Accuracy, Specificity, and Sensitivity:

Accuracy: How often do we correctly guess the movie review category? Specificity: How often do we correctly guess 0 when the true category is 0? *Sensitivity: How often do we correction guess 1 when the true category is 1?

To calculate these three quantities, we need the *confusion* matrix, which is just a two by two frequency table that tells how many times our model predicts a category by the true category.

```r
#Predict

NBClasifier_test_pred<-predict(trainedNBclassifier, newdata=fword_test)

#Confusion Matrix(reviews)
confusion=table(testY, NBClasifier_test_pred)
confusion
```

```
##      NBClasifier_test_pred
## testY   0   1
##     0 116  16
##     1  35 133
```

```r
#Accuracy
accuracy<-c(confusion[1,1]+confusion[2,2])/sum(confusion)
accuracy
```

```
## [1] 0.83
```

```r
# Specificity
specificity<-confusion[1,1]/sum(confusion[1,])
specificity
```

```
## [1] 0.8787879
```

```r
# Sensitivity
sensitivity<-confusion[2,2]/sum(confusion[2,])
sensitivity
```

```
## [1] 0.7916667
```