Homework 10

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The code below is the 'best' model for the data example that we have been running in class. For this assignment, we will be analyzing predictive distributions.

```
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
```

```
mdl <- "
model {
  for (i in 1:44){
    y[i] ~ dnorm(mu[i],1/s2g)
    mu[i] <- b0g[id[i]] + bAgeg[id[i]]*Age[i]
  }
  for (i in 45:108){
    y[i] ~ dnorm(mu[i],1/s2b)
    mu[i] <- b0b[id[i]] + bAgeb[id[i]]*Age[i]
  }
  for (i in 1:11){
    b0g[i] ~ dnorm(mub0g,1/s2intg)
    bAgeg[i] ~ dnorm(mub1g,1/s2slpg)
  }
  for (i in 1:16){
    b0b[i] ~ dnorm(mub0b,1/s2intb)
    bAgeb[i] ~ dnorm(mub1b,1/s2slpb)
  }
  s2g ~ dgamma(2,.25)
  s2b ~ dgamma(2,.25)
  s2intg ~ dgamma(4,.25)
  s2intb ~ dgamma(4,.25)
```

```
  s2slpg ~ dgamma(1.1,1)
  s2slpb ~ dgamma(1.1,1)
  mub0g ~ dnorm(0,.001)
  mub0b ~ dnorm(0,.001)
  mub1g ~ dnorm(0,.001)
  mub1b ~ dnorm(0,.001)
}
"
writeLines(mdl,'g4.txt')
y <- growth1$y
Age <- growth1$agez
id <- growth1$id
data.jags <- c('y','Age','id')
parms <- c('b0g','b0b','bAgeg','bAgeb','mub0g','mub1g','mub0b','mub1b',
           's2b','s2intb','s2slpb','s2g','s2intg','s2slpg', 'mu')
g4.sim <- jags(data=data.jags,inits=NULL,parameters.to.save = parms,
               model.file = 'g4.txt',n.iter=10000,n.burnin = 2000,
               n.thin = 2,n.chains = 4)
```

```
## module glm loaded
```

```
## Compiling model graph
##    Resolving undeclared variables
##    Allocating nodes
## Graph information:
##    Observed stochastic nodes: 108
##    Unobserved stochastic nodes: 64
##    Total graph size: 617
##
## Initializing model
```

```
g4.sim
```

```
## Inference for Bugs model at "g4.txt", fit using jags,
##  4 chains, each with 10000 iterations (first 2000 discarded), n.thin = 2
##  n.sims = 16000 iterations saved
##             mu.vect sd.vect   2.5%    25%    50%    75%  97.5% Rhat n.eff
## b0b[1]       24.764   1.005 22.761 24.095 24.779 25.443 26.698 1.001  6600
## b0b[2]       21.321   0.978 19.417 20.670 21.321 21.971 23.267 1.001  7100
## b0b[3]       22.057   0.977 20.113 21.419 22.052 22.704 24.003 1.001  4700
## b0b[4]       24.440   1.020 22.495 23.757 24.422 25.106 26.485 1.002  3900
## b0b[5]       20.967   0.987 19.057 20.307 20.968 21.629 22.911 1.001 16000
## b0b[6]       23.853   0.979 21.939 23.195 23.846 24.509 25.784 1.002  3500
## b0b[7]       21.571   0.981 19.616 20.925 21.574 22.216 23.518 1.001  8500
## b0b[8]       22.045   1.003 20.102 21.373 22.031 22.706 24.051 1.002  3600
## b0b[9]       22.600   0.977 20.664 21.957 22.618 23.251 24.496 1.001  7400
## b0b[10]      26.346   1.054 24.231 25.645 26.354 27.042 28.427 1.001  5100
## b0b[11]      21.900   1.007 19.939 21.224 21.891 22.569 23.915 1.001  4500
## b0b[12]      21.874   0.992 19.891 21.224 21.877 22.521 23.816 1.001  4600
## b0b[13]      21.109   1.119 18.844 20.369 21.151 21.872 23.219 1.001  6000
## b0b[14]      22.762   0.979 20.853 22.110 22.750 23.404 24.736 1.001  4700
## b0b[15]      23.082   0.998 21.083 22.423 23.088 23.747 25.020 1.001  5200
```

```
## b0b[16]     21.193   0.996  19.263  20.520  21.184  21.847  23.170 1.001 16000
## b0g[1]      20.172   0.555  19.079  19.803  20.177  20.535  21.284 1.001  7300
## b0g[2]      21.007   0.584  19.866  20.617  21.006  21.398  22.161 1.002  1500
## b0g[3]      21.631   0.590  20.480  21.231  21.629  22.026  22.784 1.002  3300
## b0g[4]      23.354   0.548  22.252  22.995  23.360  23.722  24.432 1.001 16000
## b0g[5]      21.542   0.556  20.452  21.177  21.539  21.906  22.640 1.001  5500
## b0g[6]      19.936   0.548  18.859  19.577  19.931  20.299  21.022 1.001  9900
## b0g[7]      21.438   0.547  20.371  21.077  21.432  21.800  22.534 1.001  7700
## b0g[8]      22.427   0.568  21.315  22.052  22.428  22.799  23.561 1.001 10000
## b0g[9]      20.121   0.565  19.001  19.746  20.119  20.490  21.249 1.002  3400
## b0g[10]     17.298   0.549  16.244  16.933  17.289  17.653  18.402 1.001 11000
## b0g[11]     24.458   0.559  23.336  24.094  24.464  24.832  25.540 1.001  9800
## bAgeb[1]     0.892   0.223   0.473   0.746   0.878   1.030   1.360 1.001 16000
## bAgeb[2]     0.747   0.215   0.303   0.612   0.751   0.884   1.170 1.001 13000
## bAgeb[3]     0.758   0.215   0.315   0.623   0.763   0.897   1.177 1.001  4800
## bAgeb[4]     0.638   0.231   0.134   0.496   0.656   0.794   1.053 1.002  1800
## bAgeb[5]     0.758   0.217   0.317   0.623   0.759   0.898   1.186 1.001 16000
## bAgeb[6]     0.779   0.214   0.354   0.643   0.780   0.913   1.208 1.002  2000
## bAgeb[7]     0.735   0.216   0.289   0.601   0.740   0.875   1.156 1.001 10000
## bAgeb[8]     0.638   0.229   0.144   0.496   0.655   0.796   1.048 1.002  2800
## bAgeb[9]     0.843   0.215   0.430   0.703   0.835   0.980   1.284 1.002  3700
## bAgeb[10]    0.870   0.226   0.440   0.724   0.859   1.006   1.353 1.002  2400
## bAgeb[11]    0.615   0.234   0.114   0.470   0.631   0.775   1.034 1.001  5900
## bAgeb[12]    0.831   0.218   0.409   0.690   0.826   0.966   1.279 1.002  3700
## bAgeb[13]    1.117   0.285   0.638   0.909   1.087   1.302   1.735 1.002  2900
## bAgeb[14]    0.700   0.220   0.235   0.561   0.713   0.847   1.111 1.001  4300
## bAgeb[15]    0.909   0.226   0.495   0.760   0.895   1.046   1.396 1.002  2900
## bAgeb[16]    0.672   0.221   0.200   0.534   0.684   0.819   1.077 1.001  5800
## bAgeg[1]     0.408   0.135   0.135   0.320   0.412   0.497   0.665 1.001  7100
## bAgeg[2]     0.665   0.148   0.386   0.563   0.661   0.763   0.962 1.003  1100
## bAgeg[3]     0.704   0.153   0.420   0.596   0.702   0.807   1.007 1.002  1800
## bAgeg[4]     0.490   0.132   0.228   0.403   0.490   0.574   0.759 1.001  9300
## bAgeg[5]     0.359   0.138   0.084   0.270   0.362   0.451   0.622 1.002  2200
## bAgeg[6]     0.406   0.134   0.136   0.321   0.408   0.495   0.666 1.001 16000
## bAgeg[7]     0.519   0.134   0.253   0.432   0.517   0.606   0.789 1.002  3700
## bAgeg[8]     0.307   0.143   0.013   0.212   0.311   0.405   0.578 1.001  4700
## bAgeg[9]     0.303   0.144   0.009   0.206   0.307   0.403   0.570 1.002  1900
## bAgeg[10]    0.430   0.134   0.156   0.344   0.433   0.520   0.692 1.001 16000
## bAgeg[11]    0.616   0.140   0.353   0.520   0.611   0.708   0.903 1.002  3600
## mu[1]       20.172   0.555  19.079  19.803  20.177  20.535  21.284 1.001  7300
## mu[2]       20.988   0.407  20.178  20.725  20.993  21.255  21.785 1.001  9100
## mu[3]       21.803   0.409  21.000  21.532  21.804  22.072  22.619 1.001 13000
## mu[4]       22.619   0.561  21.527  22.250  22.618  22.987  23.726 1.001 11000
## mu[5]       21.007   0.584  19.866  20.617  21.006  21.398  22.161 1.002  1500
## mu[6]       22.337   0.409  21.545  22.062  22.333  22.607  23.147 1.001  6000
## mu[7]       23.666   0.410  22.835  23.398  23.675  23.940  24.450 1.001  9000
## mu[8]       24.996   0.587  23.806  24.611  25.005  25.391  26.124 1.002  1800
## mu[9]       21.631   0.590  20.480  21.231  21.629  22.026  22.784 1.002  3300
## mu[10]      23.039   0.406  22.256  22.765  23.031  23.303  23.862 1.001  9200
## mu[11]      24.447   0.411  23.624  24.178  24.451  24.719  25.256 1.001  4400
## mu[12]      25.855   0.600  24.678  25.450  25.858  26.257  27.035 1.002  2200
## mu[13]      23.354   0.548  22.252  22.995  23.360  23.722  24.432 1.001 16000
## mu[14]      24.334   0.403  23.542  24.071  24.338  24.595  25.116 1.001 16000
## mu[15]      25.314   0.405  24.515  25.052  25.317  25.581  26.117 1.001 16000
```

```
## mu[16]      26.294   0.554  25.220  25.929  26.294  26.653  27.401 1.001 11000
## mu[17]      21.542   0.556  20.452  21.177  21.539  21.906  22.640 1.001  5500
## mu[18]      22.259   0.402  21.457  21.996  22.263  22.519  23.060 1.001 16000
## mu[19]      22.977   0.408  22.180  22.706  22.973  23.246  23.791 1.001  7100
## mu[20]      23.694   0.568  22.578  23.315  23.694  24.066  24.811 1.002  2900
## mu[21]      19.936   0.548  18.859  19.577  19.931  20.299  21.022 1.001  9900
## mu[22]      20.747   0.402  19.960  20.486  20.739  21.009  21.548 1.001 12000
## mu[23]      21.559   0.407  20.782  21.290  21.554  21.824  22.383 1.001 16000
## mu[24]      22.370   0.560  21.258  22.001  22.370  22.740  23.468 1.001 16000
## mu[25]      21.438   0.547  20.371  21.077  21.432  21.800  22.534 1.001  7700
## mu[26]      22.476   0.401  21.687  22.211  22.475  22.735  23.286 1.001 16000
## mu[27]      23.513   0.408  22.701  23.252  23.517  23.778  24.317 1.001 11000
## mu[28]      24.551   0.561  23.436  24.185  24.551  24.918  25.654 1.001  5200
## mu[29]      22.427   0.568  21.315  22.052  22.428  22.799  23.561 1.001 10000
## mu[30]      23.040   0.405  22.239  22.777  23.040  23.308  23.842 1.001 16000
## mu[31]      23.653   0.413  22.856  23.378  23.649  23.924  24.470 1.001 10000
## mu[32]      24.267   0.584  23.106  23.877  24.266  24.657  25.411 1.001  5600
## mu[33]      20.121   0.565  19.001  19.746  20.119  20.490  21.249 1.002  3400
## mu[34]      20.726   0.401  19.938  20.465  20.725  20.991  21.509 1.001 16000
## mu[35]      21.331   0.409  20.543  21.058  21.329  21.597  22.144 1.001 11000
## mu[36]      21.936   0.582  20.790  21.549  21.933  22.325  23.078 1.002  3100
## mu[37]      17.298   0.549  16.244  16.933  17.289  17.653  18.402 1.001 11000
## mu[38]      18.158   0.401  17.388  17.887  18.150  18.422  18.970 1.001  9600
## mu[39]      19.018   0.405  18.222  18.747  19.011  19.287  19.829 1.001 16000
## mu[40]      19.878   0.558  18.779  19.509  19.877  20.254  20.973 1.001 16000
## mu[41]      24.458   0.559  23.336  24.094  24.464  24.832  25.540 1.001  9800
## mu[42]      25.690   0.402  24.895  25.427  25.693  25.955  26.485 1.001 14000
## mu[43]      26.922   0.411  26.094  26.658  26.924  27.193  27.728 1.001  4800
## mu[44]      28.154   0.577  27.021  27.771  28.154  28.534  29.300 1.002  3300
## mu[45]      24.764   1.005  22.761  24.095  24.779  25.443  26.698 1.001  6600
## mu[46]      26.548   0.815  24.929  26.008  26.553  27.094  28.121 1.001  5900
## mu[47]      28.331   0.846  26.646  27.774  28.343  28.894  29.985 1.001  8400
## mu[48]      30.115   1.080  28.008  29.397  30.111  30.820  32.263 1.001 16000
## mu[49]      21.321   0.978  19.417  20.670  21.321  21.971  23.267 1.001  7100
## mu[50]      22.815   0.802  21.224  22.283  22.815  23.346  24.405 1.001  7500
## mu[51]      24.308   0.835  22.653  23.757  24.308  24.860  25.958 1.001 11000
## mu[52]      25.802   1.059  23.674  25.105  25.816  26.511  27.880 1.001 16000
## mu[53]      22.057   0.977  20.113  21.419  22.052  22.704  24.003 1.001  4700
## mu[54]      23.573   0.797  21.977  23.046  23.577  24.100  25.131 1.001  9500
## mu[55]      25.089   0.829  23.427  24.538  25.091  25.648  26.719 1.001 16000
## mu[56]      26.605   1.054  24.471  25.913  26.625  27.309  28.666 1.001 16000
## mu[57]      24.440   1.020  22.495  23.757  24.422  25.106  26.485 1.002  3900
## mu[58]      25.717   0.813  24.106  25.172  25.720  26.258  27.322 1.001 13000
## mu[59]      26.993   0.841  25.345  26.429  26.993  27.552  28.650 1.001 11000
## mu[60]      28.270   1.087  26.084  27.554  28.284  29.008  30.369 1.002  3900
## mu[61]      20.967   0.987  19.057  20.307  20.968  21.629  22.911 1.001 16000
## mu[62]      22.484   0.806  20.912  21.938  22.482  23.030  24.070 1.001 16000
## mu[63]      24.000   0.837  22.351  23.435  24.000  24.562  25.640 1.001 16000
## mu[64]      25.517   1.062  23.435  24.817  25.519  26.227  27.611 1.001 16000
## mu[65]      23.853   0.979  21.939  23.195  23.846  24.509  25.784 1.002  3500
## mu[66]      25.411   0.802  23.822  24.878  25.417  25.947  26.975 1.001  9500
## mu[67]      26.970   0.833  25.350  26.410  26.977  27.533  28.589 1.001 16000
## mu[68]      28.528   1.053  26.457  27.826  28.530  29.227  30.574 1.001  5700
## mu[69]      21.571   0.981  19.616  20.925  21.574  22.216  23.518 1.001  8500
```

```
## mu[70]      23.042   0.805  21.445  22.509  23.051  23.575  24.638 1.001 14000
## mu[71]      24.513   0.841  22.866  23.958  24.513  25.069  26.165 1.001 16000
## mu[72]      25.983   1.068  23.859  25.281  25.981  26.680  28.097 1.001 16000
## mu[73]      22.045   1.003  20.102  21.373  22.031  22.706  24.051 1.002  3600
## mu[74]      23.322   0.805  21.731  22.789  23.323  23.850  24.907 1.001  6200
## mu[75]      24.599   0.841  22.933  24.041  24.594  25.157  26.261 1.001  8800
## mu[76]      25.876   1.089  23.679  25.156  25.890  26.611  27.956 1.001  5800
## mu[77]      22.600   0.977  20.664  21.957  22.618  23.251  24.496 1.001  7400
## mu[78]      24.286   0.801  22.709  23.755  24.291  24.820  25.862 1.001 14000
## mu[79]      25.973   0.836  24.323  25.407  25.966  26.534  27.626 1.001 11000
## mu[80]      27.659   1.062  25.595  26.938  27.651  28.362  29.788 1.001  6300
## mu[81]      26.346   1.054  24.231  25.645  26.354  27.042  28.427 1.001  5100
## mu[82]      28.086   0.851  26.403  27.520  28.090  28.653  29.757 1.001 16000
## mu[83]      29.825   0.864  28.119  29.255  29.828  30.408  31.530 1.001 16000
## mu[84]      31.565   1.085  29.434  30.845  31.560  32.274  33.728 1.001  6900
## mu[85]      21.900   1.007  19.939  21.224  21.891  22.569  23.915 1.001  4500
## mu[86]      23.129   0.803  21.534  22.598  23.122  23.667  24.722 1.001  8200
## mu[87]      24.359   0.844  22.699  23.794  24.354  24.920  26.016 1.001 16000
## mu[88]      25.588   1.105  23.333  24.857  25.610  26.325  27.694 1.001 16000
## mu[89]      21.874   0.992  19.891  21.224  21.877  22.521  23.816 1.001  4600
## mu[90]      23.535   0.804  21.960  22.998  23.533  24.065  25.137 1.001 10000
## mu[91]      25.197   0.830  23.580  24.624  25.200  25.742  26.849 1.001 16000
## mu[92]      26.858   1.053  24.843  26.149  26.846  27.546  28.976 1.001 16000
## mu[93]      21.109   1.119  18.844  20.369  21.151  21.872  23.219 1.001  6000
## mu[94]      23.342   0.821  21.732  22.793  23.344  23.886  24.959 1.001 16000
## mu[95]      25.576   0.864  23.851  24.994  25.582  26.153  27.268 1.001 11000
## mu[96]      27.809   1.213  25.549  26.971  27.773  28.613  30.281 1.001  4900
## mu[97]      22.762   0.979  20.853  22.110  22.750  23.404  24.736 1.001  4700
## mu[98]      24.161   0.798  22.602  23.633  24.165  24.693  25.726 1.001  7200
## mu[99]      25.560   0.839  23.909  25.002  25.558  26.117  27.230 1.001 11000
## mu[100]     26.959   1.077  24.791  26.249  26.961  27.681  29.077 1.001  8700
## mu[101]     23.082   0.998  21.083  22.423  23.088  23.747  25.020 1.001  5200
## mu[102]     24.899   0.805  23.331  24.360  24.901  25.427  26.477 1.001 14000
## mu[103]     26.716   0.841  25.043  26.155  26.718  27.285  28.352 1.001 15000
## mu[104]     28.533   1.084  26.438  27.806  28.519  29.250  30.710 1.001  6100
## mu[105]     21.193   0.996  19.263  20.520  21.184  21.847  23.170 1.001 16000
## mu[106]     22.537   0.810  20.961  21.996  22.522  23.074  24.133 1.001 16000
## mu[107]     23.880   0.843  22.251  23.309  23.870  24.433  25.557 1.001 16000
## mu[108]     25.223   1.076  23.091  24.513  25.231  25.939  27.319 1.001 11000
## mub0b       22.619   0.689  21.234  22.173  22.620  23.075  23.972 1.001 11000
## mub0g       21.194   0.869  19.442  20.647  21.183  21.759  22.919 1.001  9600
## mub1b        0.782   0.119   0.545   0.705   0.781   0.861   1.014 1.002  1800
## mub1g        0.474   0.091   0.289   0.418   0.474   0.530   0.653 1.001 16000
## s2b          2.813   0.645   1.784   2.348   2.733   3.184   4.287 1.001  4500
## s2g          0.594   0.194   0.319   0.455   0.561   0.693   1.062 1.001  8200
## s2intb       5.756   2.788   2.054   3.795   5.185   7.086  12.792 1.001 15000
## s2intg       8.018   3.897   2.883   5.197   7.221   9.914  17.764 1.001 16000
## s2slpb       0.084   0.082   0.003   0.030   0.062   0.112   0.291 1.001  6900
## s2slpg       0.065   0.074   0.005   0.026   0.047   0.080   0.225 1.008   430
## deviance   339.471  13.285 314.921 330.308 338.957 348.111 366.736 1.001  8000
##
## 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).
##
```

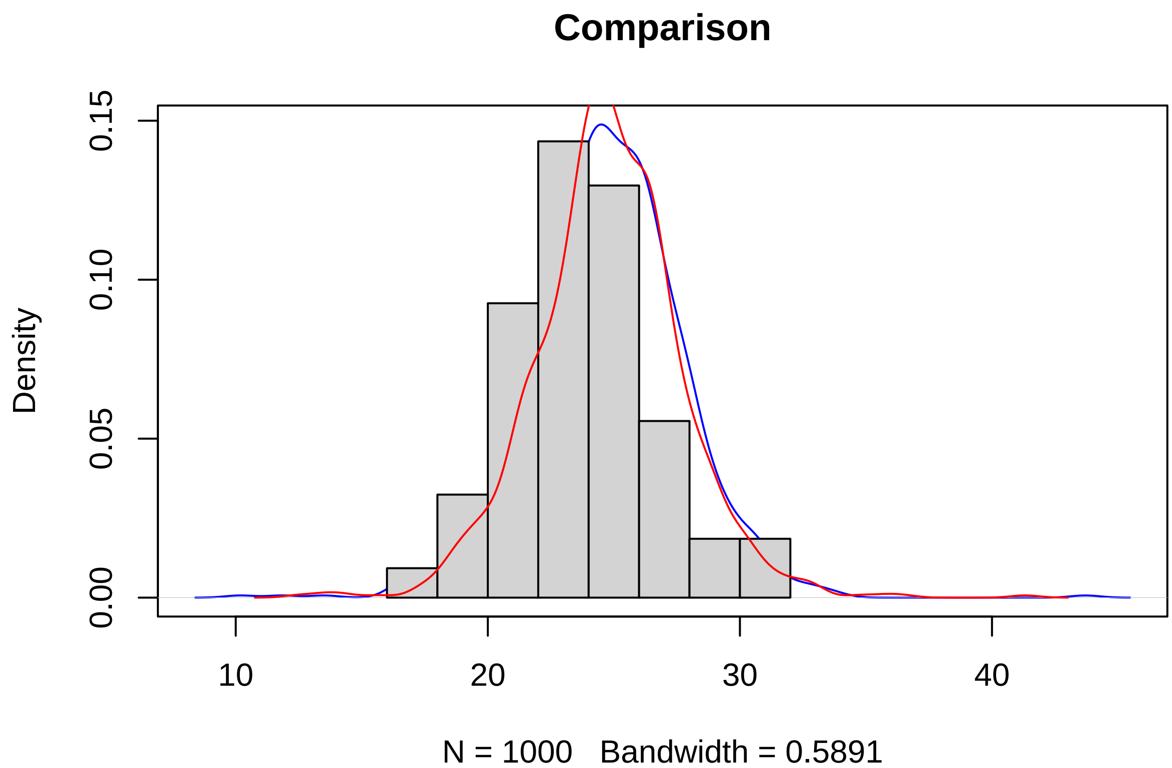
```
## DIC info (using the rule, pD = var(deviance)/2)
## pD = 88.2 and DIC = 427.7
## DIC is an estimate of expected predictive error (lower deviance is better).
```

1. Draw from separate prior predictive distributions for the girls and boys. Graph these distributions on a plot with histograms of the actual boy and girl data.

```
n <- 1000
mub0g <- rnorm(n, 0,.001)
mub1g <- rnorm(n, 0,.001)
mub0b <- rnorm(n, 0,.001)
mub1b <- rnorm(n, 0,.001)
s2b <- rgamma(n, 2, 0.25)
s2intb <- rgamma(n, 4,.25)
s2slpb <- rgamma(n, 1.1,1)
s2g <- rgamma(n, 2, 0.25)
s2intg <- rgamma(n, 4,.25)
s2slpg <- rgamma(n, 1.1,1)
b0g <- dnorm(mub0g, sqrt(s2intg))
b0b <- dnorm(mub0b,sqrt(s2intb))
bAgeg <- dnorm(mub1g, sqrt(s2slpg))
bAgeb <- dnorm(mub1b,sqrt(s2slpb))

yb <- b0b + bAgeb*seq(0,6, by=2) + rnorm(n, 24, sqrt(s2b))
yg <- b0g + bAgeg*seq(0,6, by=2) + rnorm(n, 24, sqrt(s2g))

plot(x = density(yb), col='blue', main = 'Comparison')
hist(growth1$y, freq = FALSE, add = T)
lines(density(yg), col = 'red')
```



Blue is for boys, red for girls.

2. Make observations about the differences between the prior predictive distributions and the true data.

It seems that there is very little differences, probably because they have essentially the same prior.

3. Write 2-5 sentences about the importance of understanding data when choosing prior distributions.

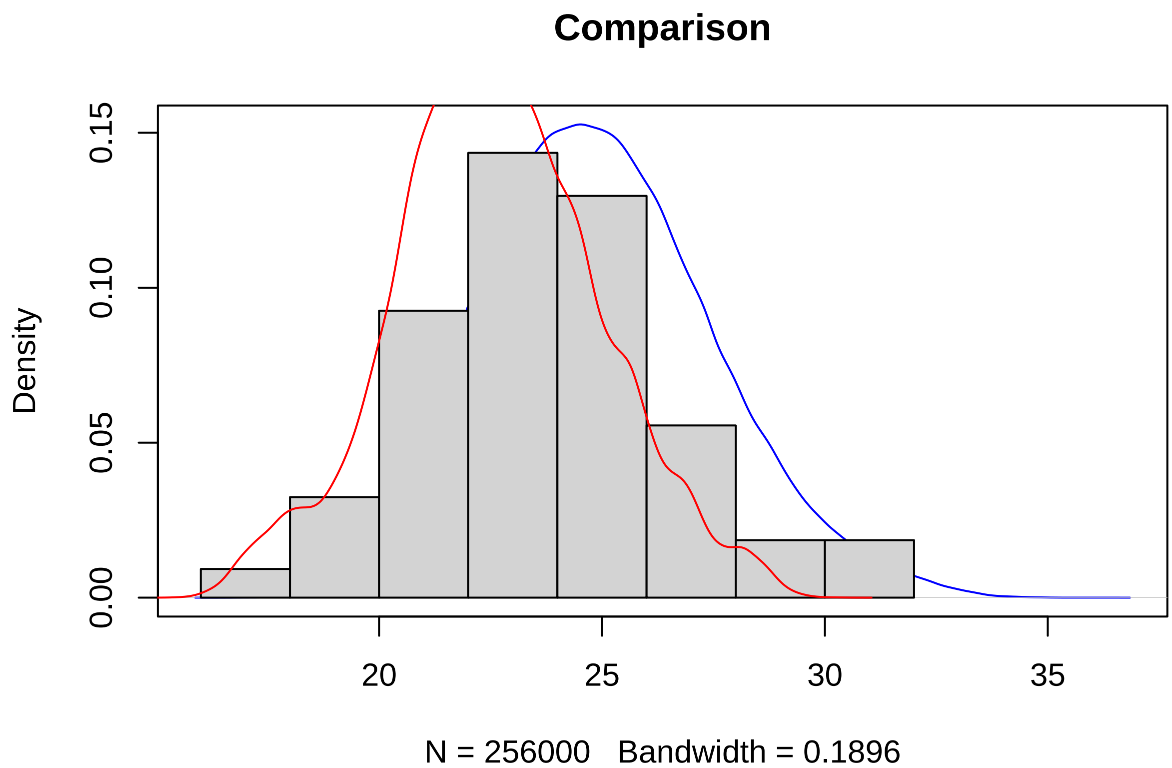
I think it's important that we understand how the different categories in our data compare. If there are measureable differences, we should probably include that information in a weakly informative prior.

4. Draw from the posterior distributions of boys and girls. Graph these distributions on a plot with the actual data as in problem 1.

```
library(coda)
samples <- coda.samples(g4.sim$model,c('mu'), n.iter = 1000)
sims <- as.matrix(samples)

yg <- sims[,1:44]
yb <- sims[,45:108]

plot(x = density(yb), col='blue', main = 'Comparison')
hist(growth1$y, freq = FALSE, add = T)
lines(density(yg), col = 'red')
```



5. Make observations about the differences between the posterior predictive distributions and the true data.

The posterior predictive makes much more sense, and matches more closely with the data. In particular, there is a clearer difference between the boys and the girls for our predicted values.

6. Write 2-5 sentences about the model we are fitting (i.e. what the different parameters are, why we fit them, what difference they make, etc. This is very open-ended, just trying to get you to think hard about what we are modeling.)

In general, it's really important that we accurately model our data. In essence, modeling is an iterative approach to learning and understanding the data source we are pulling from. I think it's important that we gain understanding throughout the process, rather than approaching this as merely a means to an end.