## Wulfing\_HW04

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## R Question 1

Using either the Swiss hare dataset or your own data, run a Bayesian t-test OR a simple linear regression using JAGS.

Hi sorry, I know you said to use our own data but I'm still in the middle of a data pull. I'll hopefully have some for next assignment but for now, hares. Also turns out elevation is not a very good predictor of hare density lol.

```
hares <- hares_data %>% drop_na(elevation) %>% drop_na(mean.density)
\#sink("HW4\_model.txt") \ \#Had \ to \ comment \ this \ out \ so \ markdown \ would \ knit
 cat("model { #always start JAGS with this model line
     # Priors-all things we don't know
     beta0 \sim dnorm(0,0.01)
                                 # precision inverse of variance. This means huge variance
     beta1 ~ dnorm(0,0.01)
     precision <- 1 / variance #Priors are unknown. We only know mass and svl
     variance <- sigma^2</pre>
     sigma ~ dunif(0,15) #I just kept 15 cause that's what I've been using
     #No prior for mew. We will calc further down. We've covered mew using priors for b0 and b1
     # Likelihood
     for(i in 1:nobs){
     mean.density[i] ~ dnorm(mu[i], precision) #mass - > density
     mu[i] <- beta0 + beta1 * elevation[i] #svl-> elevation
     } # i loop
     } # end of the model.
     ",fill=TRUE)
```

```
## model { #always start JAGS with this model line
##

## # Priors-all things we don't know

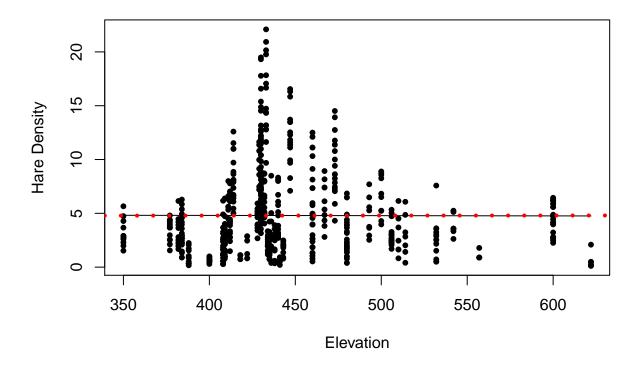
## beta0 ~ dnorm(0,0.01) # precision inverse of variance. This means huge variance
## beta1 ~ dnorm(0,0.01)

## precision <- 1 / variance #Priors are unknown. We only know mass and svl
## variance <- sigma^2</pre>
```

```
##
        sigma ~ dunif(0,15) #I just kept 15 cause that's what I've been using
##
        #No prior for mew. We will calc further down. We've covered mew using priors for b0 and b1
##
##
##
        # Likelihood
##
        for(i in 1:nobs){
##
        mean.density[i] ~ dnorm(mu[i], precision) #mass - > density
##
##
        mu[i] <- beta0 + beta1 * elevation[i] #svl-> elevation
##
##
        } # i loop
##
        } # end of the model.
##
##
#sink() #I had to comment this out to get markdown to knit
# Bundle data
win.data <- list(mean.density = hares$mean.density,</pre>
                 elevation = hares$elevation,
                 nobs = nrow(hares))
# Function to generate starting values aka initial values. Supply init vals
inits <- function()list(beta0 = rnorm(1),</pre>
                        sigma = runif(1, 0, 15))
# Parameters to be monitored (= to estimate)
params <- c("beta0",
            "beta1",
            "sigma")
# MCMC settings
nc <- 3
ni <- 1000
nb <- 1
nt <- 1
out <- jags(win.data, inits, params, "HW4_model.txt", n.chains = nc,
            n.thin = nt, n.iter = ni, n.burnin = nb, working.directory = getwd())
## module glm loaded
## Compiling model graph
##
      Resolving undeclared variables
##
      Allocating nodes
## Graph information:
      Observed stochastic nodes: 608
##
##
      Unobserved stochastic nodes: 3
##
      Total graph size: 1307
##
## Initializing model
```

```
print(out, dig =2)
## Inference for Bugs model at "HW4_model.txt", fit using jags,
## 3 chains, each with 1000 iterations (first 1 discarded)
## n.sims = 2997 iterations saved
##
           mu.vect sd.vect
                              2.5%
                                       25%
                                                50%
                                                        75%
                                                              97.5% Rhat n.eff
## beta0
               4.77
                       1.25
                               2.41
                                       3.93
                                               4.76
                                                       5.60
                                                               7.34 1.00 3000
              0.00
                       0.00
                             -0.01
                                       0.00
                                               0.00
                                                       0.00
                                                               0.01 1.00
                                                                          3000
## beta1
## sigma
              3.96
                      0.12
                               3.74
                                       3.87
                                               3.95
                                                       4.03
                                                               4.19 1.00 2700
## deviance 3397.08
                      3.87 3394.30 3395.24 3396.39 3398.14 3403.03 1.12 3000
## 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 = 7.5 and DIC = 3404.6
## DIC is an estimate of expected predictive error (lower deviance is better).
m <- lm(mean.density ~ elevation, hares)</pre>
summary(m)
##
## Call:
## lm(formula = mean.density ~ elevation, data = hares)
## Residuals:
##
     Min
              1Q Median
                            3Q
## -4.636 -2.804 -1.121 1.664 17.294
## Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
## (Intercept) 4.8932139 1.2907686 3.791 0.000165 ***
## elevation -0.0002183 0.0028707 -0.076 0.939405
## ---
## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' 1
## Residual standard error: 3.951 on 606 degrees of freedom
## Multiple R-squared: 9.544e-06, Adjusted R-squared: -0.001641
## F-statistic: 0.005783 on 1 and 606 DF, p-value: 0.9394
elevation_p <- seq(min(hares$elevation), max(hares$elevation),length.out = length(hares$elevation))
elevation_preds <- m$coefficients[1] + m$coefficients[2]*elevation_p
plot(hares$mean.density ~ hares$elevation,
     ylab = "Hare Density",
     xlab = "Elevation",
    pch = 20)
lines(elevation_preds ~ elevation_p)
abline(a =out$BUGSoutput$mean$beta0,
```

```
b = out$BUGSoutput$mean$beta1,
lwd = 4,lty = 3, col = "red")
```



# plot. Bayes vs linear mocel from above. Black is truth, blue is lm, red is bayes

## **BONUS**

Fit a means parameterization of a t-test in JAGS, either to the Swiss hares data, simulation data, or your own data. Hint: see page 120-121 of Kéry 2010 regarding double indexing syntax

Ok I have no idea how to actually do this. I figured out the alpha indexing thing but couldn't get the equation quite right until class today. However, when I set up the matrix (d) it still down't look right. Is it a model issue or am I just setting up that matrix incorrectly?

```
bonus_hares <- hares_data %>%
        drop_na(landuse) %>%
        drop_na(mean.density )
for(i in 1:nrow(bonus_hares)){
        if(bonus_hares$landuse[i] == "arable"){
                 bonus_hares$x[i] <- 1
        }
        else{ # if(bonus_hares$landuse[i] == "qrass")
                 bonus_hares$x[i] <- 2
        }
}
# bonus_hares
#
# data_sum <- bonus_hares %>%
          group_by(landuse) %>%
#
          summarise_at(vars(mean.density), list(name = mean, sd))
# mu1 <- as.numeric(data_sum[1,2]) #Arable land mean</pre>
# mu2 <- as.numeric(data_sum[2,2]) #Grassland mean</pre>
# sigma1 <- as.numeric(data_sum[1,3]) #Arable land sd</pre>
# sigma2 <- as.numeric(data_sum[2,3]) #Grassland sd</pre>
#sink("HW4_bonusModel.txt")
cat("
    model {
    # PRIORS
    for(j in 1:nsites){
      alpha[j] ~ dnorm(0,0.001)
      tau[j] <- 1/sigma[j]^2</pre>
      sigma[j] ~ dunif(0,10)
    # LIKELIHOOD
    for(i in 1:n){
      y[i] ~ dnorm(mu[i],tau[x[i]])
      #mu[i] <- alpha0 + alpha1*x[i]</pre>
      mu[i] <- alpha[x[i]]</pre>
    }
```

```
diff12 <- alpha[2] - alpha[1]</pre>
    for(i in 1:nsites){
    avg[i] <- (alpha[i]*stdev_data) + mean_data</pre>
    stan_dev[i] <- (sigma[i]*stdev_data)</pre>
    }
    } # end of model
    ",fill = TRUE)
##
##
       model {
##
##
       # PRIORS
       for(j in 1:nsites){
##
##
         alpha[j] ~ dnorm(0,0.001)
##
         tau[j] <- 1/sigma[j]^2
##
         sigma[j] ~ dunif(0,10)
##
##
##
       # LIKELIHOOD
##
       for(i in 1:n){
         y[i] ~ dnorm(mu[i],tau[x[i]])
##
##
##
         #mu[i] <- alpha0 + alpha1*x[i]</pre>
##
         mu[i] <- alpha[x[i]]</pre>
##
##
       }
##
##
       diff12 <- alpha[2] - alpha[1]
##
##
       for(i in 1:nsites){
       avg[i] <- (alpha[i]*stdev_data) + mean_data</pre>
##
##
       stan_dev[i] <- (sigma[i]*stdev_data)</pre>
##
##
       } # end of model
##
##
#sink()
win.data <- list(y= bonus_hares$mean.density,</pre>
                  n = nrow(bonus_hares),
                  x = bonus_hares$x,
                  nsites = length(unique(bonus_hares$x)),#This is just going to be 2
                  stdev_data = sd(bonus_hares$mean.density),
                  mean_data = mean(bonus_hares$mean.density))
# Initial values
inits <- function()list(alpha = rnorm(length(unique(bonus_hares$x))),</pre>
                          sigma = rlnorm(length(unique(bonus_hares$x))))
```

# Parameters monitored

```
params <- c("alpha",
            "sigma",
            "diff12",
            "avg",
            "stan_dev"
)
# MCMC settings
ni <- 10000; nt <- 1; nb <- 1000; nc <- 3
out <- jags(win.data, inits, params, "HW4_bonusModel.txt",
            n.chains = nc, n.thin = nt, n.iter = ni, n.burnin = nb,
            working.directory = getwd())
## Compiling model graph
      Resolving undeclared variables
##
      Allocating nodes
## Graph information:
##
      Observed stochastic nodes: 677
##
      Unobserved stochastic nodes: 4
##
      Total graph size: 1378
## Initializing model
print(out, dig = 2)
## Inference for Bugs model at "HW4_bonusModel.txt", fit using jags,
## 3 chains, each with 10000 iterations (first 1000 discarded)
## n.sims = 27000 iterations saved
##
              mu.vect sd.vect
                                  2.5%
                                           25%
                                                   50%
                                                           75%
                                                                 97.5% Rhat n.eff
## alpha[1]
                 5.33
                        0.18
                                  4.98
                                          5.21
                                                  5.33
                                                          5.46
                                                                 5.69
                                                                          1 27000
                 3.19
                          0.18
                                  2.83
                                        3.06
                                                  3.19
                                                          3.31
                                                                  3.55
                                                                          1 27000
## alpha[2]
                                       24.62
## avg[1]
                 25.09
                          0.70
                                 23.74
                                                 25.08
                                                         25.56
                                                                 26.46
                                                                          1 27000
## avg[2]
                 16.91
                         0.70
                               15.53 16.43 16.91 17.38
                                                                 18.28
                                                                          1 27000
## diff12
                 -2.14
                         0.26
                                 -2.65
                                       -2.32
                                                 -2.14
                                                         -1.97
                                                                 -1.64
                                                                          1 27000
## sigma[1]
                 4.07
                         0.13
                                 3.82
                                         3.98
                                                 4.07
                                                          4.16
                                                                  4.34
                                                                          1 16000
## sigma[2]
                 2.53
                         0.13
                                  2.28
                                         2.44
                                                  2.52
                                                          2.61
                                                                  2.80
                                                                          1 10000
                         0.50
                                 14.59
                                         15.20
                                                 15.53
                                                         15.87
                                                                 16.56
                                                                          1 16000
## stan_dev[1]
                 15.54
## stan dev[2]
                 9.64
                          0.51
                                  8.71
                                          9.30
                                                  9.62
                                                          9.97
                                                                          1 10000
                                                                 10.71
                          2.90 3636.31 3637.78 3639.21 3641.25 3647.26
## deviance
              3639.88
                                                                          1 5000
## 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 = 4.2 and DIC = 3644.1
## DIC is an estimate of expected predictive error (lower deviance is better).
# FIX THISsee the full columns of the design matrix and linear algebra
d <- data.frame(density = round(bonus hares$mean.density,1),</pre>
           int = rep(1,length(bonus_hares$mean.density)),
```

```
alpha1 = round(rep(out$BUGSoutput$mean$alpha[1], length(bonus_hares$mean.density)),1),
    landuse = bonus_hares$x,
    alpha2 = round(rep(out$BUGSoutput$mean$alpha[2], length(bonus_hares$mean.density)),1))
    #resid = round(out$BUGSoutput$mean$resid,1))
print(d)
```

##		density	int	alpha1	landuse	alpha2
##	1	2.7	1	5.3	1	3.2
##	2	3.1	1	5.3	1	3.2
##	3	1.3	1	5.3	1	3.2
##	4	0.9	1	5.3	1	3.2
##	5	1.3	1	5.3	1	3.2
##	6	2.7	1	5.3	1	3.2
##	7	2.2	1	5.3	1	3.2
##	8	3.6	1	5.3	1	3.2
##	9	5.4	1	5.3	1	3.2
##	10	6.3	1	5.3	1	3.2
##	11	4.9	1	5.3	1	3.2
##	12	2.7	1	5.3	1	3.2
##	13	2.2	1	5.3	1	3.2
##	14	0.9	1	5.3	1	3.2
##	15	2.8	1	5.3	1	3.2
##	16	2.5	1	5.3	1	3.2
##	17	2.0	1	5.3	1	3.2
##	18	2.0	1	5.3	1	3.2
##	19	2.2	1	5.3	1	3.2
##	20	3.9	1	5.3	1	3.2
##	21	4.5	1	5.3	1	3.2
##	22	6.1	1	5.3	1	3.2
##	23	3.6	1	5.3	1	3.2
##	24	4.2	1	5.3	1	3.2
##	25	2.2	1	5.3	1	3.2
##	26	2.5	1	5.3	1	3.2
##	27	1.7	1	5.3	1	3.2
##	28	2.2	1	5.3	1	3.2
##	29	5.8	1	5.3	1	3.2
##	30	4.0	1	5.3	1	3.2
##	31	2.9	1	5.3	1	3.2
##	32	1.5	1	5.3	1	3.2
##	33	2.9	1	5.3	1	3.2
##	34	2.7	1	5.3	1	3.2
##	35	2.1	1	5.3	1	3.2
##	36	2.5	1	5.3	1	3.2
##	37	4.6	1	5.3	1	3.2
##	38	4.6	1	5.3	1	3.2
##	39	2.9	1	5.3	1	3.2
##	40	2.3	1	5.3	1	3.2
##	41	2.9	1	5.3	1	3.2
##	42	4.2	1	5.3	1	3.2
##	43	2.1	1	5.3	1	3.2
##	44	0.9	1	5.3	1	3.2
##	45	0.2	1	5.3	1	3.2

##	46	0.3	1	5.3	1	3.2
##	47	0.3	1	5.3	1	3.2
##	48	0.3	1	5.3	1	3.2
##	49	0.5	1	5.3	1	3.2
##	50	1.7	1	5.3	1	3.2
##	51	1.0	1	5.3	1	3.2
##	52	1.6	1	5.3	1	3.2
##	53	0.9	1	5.3	1	3.2
##	54	2.2	1	5.3	1	3.2
##	55	4.5	1	5.3	1	3.2
##	56	6.1	1	5.3	1	3.2
##	57	2.5	1	5.3	1	3.2
##	58	1.6	1	5.3	1	3.2
##	59	3.7	1	5.3	1	3.2
##	60	1.6	1	5.3	1	3.2
##	61	0.8	1	5.3	1	3.2
##	62	4.9	1	5.3	1	3.2
##	63	6.1	1	5.3	1	3.2
##	64	2.8	1	5.3	1	3.2
##	65	3.2	1	5.3	1	3.2
##	66	1.4	1	5.3	1	3.2
##	67	2.0	1	5.3	1	3.2
##	68	0.4	1	5.3	1	3.2
##	69	0.9	1	5.3	2	3.2
##	70	0.9	1	5.3	2	3.2
##	71	0.9	1	5.3	2	3.2
##	72	0.9	1	5.3	2	3.2
##	73	1.8	1	5.3	2	3.2
##	74	2.5	1	5.3	1	3.2
##	75	3.6	1	5.3	1	3.2
##	76	2.2	1	5.3	1	3.2
##	77	3.2	1	5.3	1	3.2
##	78	2.9	1	5.3	1	3.2
##	79	7.6	1	5.3	1	3.2
##	80	0.7	1	5.3	1	3.2
##	81	3.0	1	5.3	2	3.2
##	82	2.5	1	5.3	2	3.2
					_	
##	83 84	0.5 3.6	1 1	5.3 5.3	2	3.2
##	85 86	0.5 1.5	1	5.3	2	3.2
##	86		1	5.3	2	3.2
##	87	3.3	1	5.3	2	3.2
##	88	3.6	1	5.3	2	3.2
##	89	5.1	1	5.3	2	3.2
##	90	5.2	1	5.3	2	3.2
##	91	3.6	1	5.3	2	3.2
##	92	3.6	1	5.3	2	3.2
##	93	2.6	1	5.3	2	3.2
##	94	2.9	1	5.3	1	3.2
##	95	3.3	1	5.3	1	3.2
##	96	3.3	1	5.3	1	3.2
##	97	1.6	1	5.3	1	3.2
##	98	2.5	1	5.3	1	3.2
##	99	2.0	1	5.3	1	3.2

##	100	2.4	1	5.3	1	3.2
##	101	2.0	1	5.3	1	3.2
##	102	2.7	1	5.3	1	3.2
##	103	2.5	1	5.3	1	3.2
##	104	1.2	1	5.3	1	3.2
##	105	2.2	1	5.3	1	3.2
##	106	1.4	1	5.3	1	3.2
##	107	2.0	1	5.3	1	3.2
##	108	2.0	1	5.3	1	3.2
##	109	2.7	1	5.3	1	3.2
##	110	8.0	1	5.3	1	3.2
##	111	8.0	1	5.3	1	3.2
##	112	8.7	1	5.3	1	3.2
##	113	8.7	1	5.3	1	3.2
##	114	7.9	1	5.3	1	3.2
##	115	5.5	1	5.3	1	3.2
##	116	5.0	1	5.3	1	3.2
##	117	5.1	1	5.3	1	3.2
##	118	4.0	1	5.3	1	3.2
##	119	5.0	1	5.3	1	3.2
##	120	6.0	1	5.3	1	3.2
##	121	6.7	1	5.3	1	3.2
##	122	4.6	1	5.3	1	3.2
##	123	6.5	1	5.3	1	3.2
##	124	19.8	1	5.3	1	3.2
##	125	13.2	1	5.3	1	3.2
##	126	20.9	1	5.3	1	3.2
##	127	17.1	1	5.3	1	3.2
##	128	14.3	1	5.3	1	3.2
##	129	17.8	1	5.3	1	3.2
##	130	20.2	1	5.3	1	3.2
##	131	20.2	1	5.3	1	3.2
##	132	14.3	1	5.3	1	
##	133	13.2	1		1	3.2
				5.3		3.2
## ##	134 135	14.7	1 1	5.3	1 1	3.2
		16.7		5.3		3.2
##	136	14.3	1	5.3	1	3.2
##	137	12.8	1	5.3	1	3.2
##	138	12.8	1	5.3	1	3.2
##	139	9.7	1	5.3	1	3.2
##	140	11.6	1	5.3	1	3.2
##	141	3.2	1	5.3	1	3.2
##	142	4.6	1	5.3	1	3.2
##	143	4.0	1	5.3	1	3.2
##	144	4.6	1	5.3	1	3.2
##	145	5.7	1	5.3	1	3.2
##	146	6.9	1	5.3	1	3.2
##	147	11.5	1	5.3	1	3.2
##	148	8.9	1	5.3	1	3.2
##	149	8.6	1	5.3	1	3.2
##	150	7.2	1	5.3	1	3.2
##	151	6.3	1	5.3	1	3.2
##	152	4.3	1	5.3	1	3.2
##	153	6.3	1	5.3	1	3.2

##	154	4.9	1	5.3	1	3.2
##	155	5.4	1	5.3	1	3.2
##	156	4.6	1	5.3	1	3.2
##	157	5.4	1	5.3	1	3.2
##	158	3.5	1	5.3	1	3.2
##	159	4.7	1	5.3	1	3.2
##	160	4.8	1	5.3	1	3.2
##	161	4.2	1	5.3	1	3.2
##	162	4.7	1	5.3	1	3.2
##	163	6.8	1	5.3	1	3.2
##	164	8.1	1	5.3	1	3.2
##	165	9.3	1	5.3	1	3.2
##	166	7.5	1	5.3	1	3.2
##	167	7.2	1	5.3	1	3.2
##	168	7.2	1	5.3	1	3.2
##	169	7.3	1	5.3	1	3.2
##	170	6.2	1	5.3	1	3.2
##	171	7.2	1	5.3	1	3.2
##	172	4.8	1	5.3	1	3.2
##	173	2.0	1	5.3	1	3.2
##	174	1.8	1	5.3	1	3.2
##	175	0.8	1	5.3	1	3.2
##	176	1.4	1	5.3	1	3.2
##	177	1.8	1	5.3	1	3.2
##	178	3.2	1	5.3	1	3.2
##	179	1.6	1	5.3	1	3.2
##	180	1.0	1	5.3	1	3.2
##	181	1.4	1	5.3	1	3.2
##	182	2.0	1	5.3	1	3.2
##	183	1.0	1	5.3	1	3.2
##	184	0.4	1	5.3	1	3.2
##	185	0.4	1	5.3	1	3.2
##	186	2.2	1	5.3	1	3.2
##	187	3.9	1	5.3	1	3.2
##	188	4.4	1	5.3	1	3.2
##	189	3.9	1	5.3	1	3.2
##	190	6.5	1	5.3	1	3.2
##	191	6.5	1	5.3	1	3.2
##	192	6.8	1	5.3	1	3.2
##	193	4.2	1	5.3	1	3.2
##	194	4.9	1	5.3	1	3.2
##	195	3.3	1	5.3	1	3.2
##	196	2.3	1	5.3	1	3.2
##	197	2.6	1	5.3	1	3.2
##	198	3.7	1	5.3	1	3.2
##	199	2.5	1	5.3	1	3.2
##	200	2.9	1	5.3	1	3.2
##	201	3.7	1	5.3	1	3.2
##	202	5.3	1	5.3	1	3.2
##	203	5.6	1	5.3	1	3.2
##	204	7.7	1	5.3	1	3.2
##	205	6.5	1	5.3	1	3.2
##	206	3.6	1	5.3	1	3.2
##	207	8.5	1	5.3	1	3.2
		5.5	-		-	0.2

##	208	5.0	1	5.3	1	3.2
##	209	4.2	1	5.3	1	3.2
##	210	5.0	1	5.3	1	3.2
##	211	2.7	1	5.3	1	3.2
##	212	1.9	1	5.3	1	3.2
	213		1	5.3	1	
##		0.4				3.2
##	214	2.9	1	5.3	1	3.2
##	215	2.5	1	5.3	1	3.2
##	216	1.2	1	5.3	1	3.2
##	217	0.8	1	5.3	1	3.2
##	218	0.8	1	5.3	1	3.2
##	219	2.9	1	5.3	1	3.2
##	220	2.8	1	5.3	1	3.2
##	221	2.3	1	5.3	1	3.2
##	222	2.8	1	5.3	1	3.2
##	223	2.9	1	5.3	1	3.2
##	224	4.7	1	5.3	1	3.2
##	225	5.7	1	5.3	1	3.2
##	226	4.3	1	5.3	1	3.2
##	227	3.7	1	5.3	1	3.2
##						
	228	2.6	1	5.3	1	3.2
##	229	2.9	1	5.3	1	3.2
##	230	1.5	1	5.3	1	3.2
##	231	2.8	1	5.3	1	3.2
##	232	2.0	1	5.3	1	3.2
##	233	4.7	1	5.3	2	3.2
##	234	4.7	1	5.3	2	3.2
##	235	4.2	1	5.3	2	3.2
##	236	4.7	1	5.3	2	3.2
##	237	4.9	1	5.3	2	3.2
##	238	4.2	1	5.3	2	3.2
##	239	4.0	1	5.3	2	3.2
##	240	6.2	1	5.3	2	3.2
##	241	5.9	1	5.3	2	3.2
##	242	4.4	1	5.3	2	3.2
##	242	6.2	1	5.3	2	3.2
##	244	5.6	1	5.3	2	3.2
##	245	6.2	1	5.3	2	3.2
##	246	0.8	1	5.3	2	3.2
##	247	0.5	1	5.3	2	3.2
##	248	0.3	1	5.3	2	3.2
##	249	0.5	1	5.3	2	3.2
##	250	0.7	1	5.3	2	3.2
##	251	0.6	1	5.3	2	3.2
##	252	0.6	1	5.3	2	3.2
##	253	0.6	1	5.3	2	3.2
##	254	0.9	1	5.3	2	3.2
##	255	0.7	1	5.3	2	3.2
##	256	0.6	1	5.3	2	3.2
##	257	1.0	1	5.3	2	3.2
##	258	1.0	1	5.3	2	3.2
					1	
##	259	0.9	1	5.3		3.2
##	260	0.8	1	5.3	1	3.2
##	261	1.8	1	5.3	1	3.2

##	262	1.9	1	5.3	1	3.2
##	263	2.4	1	5.3	1	3.2
##	264	1.4	1	5.3	1	3.2
##	265	2.5	1	5.3	1	3.2
##	266	2.1	1	5.3	1	3.2
##	267	2.0	1	5.3	1	3.2
##	268	2.0	1	5.3	1	3.2
##	269	0.2	1	5.3	1	3.2
##	270	0.9	1	5.3	1	3.2
##	271	0.8	1	5.3	1	3.2
##	272	0.8	1	5.3	1	3.2
##			1		1	3.2
	273	0.5		5.3		
##	274	0.6	1	5.3	1	3.2
##	275	0.4	1	5.3	1	3.2
##	276	1.5	1	5.3	1	3.2
##	277	1.7	1	5.3	1	3.2
##	278	3.0	1	5.3	1	3.2
##	279	2.5	1	5.3	1	3.2
##	280	3.9	1	5.3	1	3.2
##	281	3.6	1	5.3	1	3.2
##	282	3.1	1	5.3	1	3.2
##	283	2.8	1	5.3	1	3.2
##	284	7.4	1	5.3	1	3.2
##	285	7.7	1	5.3	1	3.2
##	286	8.7	1	5.3	1	3.2
##	287	8.5	1	5.3	1	3.2
##	288	4.6	1	5.3	1	3.2
##	289	6.7	1	5.3	1	3.2
##	290	8.4	1	5.3	1	3.2
##	291	12.1	1	5.3	1	3.2
##	292	16.6	1	5.3	1	3.2
##	293	17.8	1	5.3	1	3.2
##	294	14.9	1	5.3	1	3.2
##	295	12.0	1	5.3	1	3.2
##	296	15.4	1	5.3	1	3.2
##	297	19.5	1	5.3	1	3.2
##	298	19.3	1	5.3	1	3.2
##	299	14.5	1	5.3	1	3.2
##	300	13.2	1	5.3	1	3.2
##	301	8.6	1	5.3	1	3.2
##	302	11.4	1	5.3	1	3.2
##	303	9.4	1	5.3	1	3.2
##	304	10.8	1	5.3	1	3.2
##	305	7.3	1	5.3	1	3.2
##	306	7.5	1	5.3	1	3.2
##	307	7.1	1	5.3	1	3.2
##	308	8.6	1	5.3	1	3.2
##	309	7.8	1	5.3	1	3.2
##	310	5.9	1	5.3	1	3.2
##	311	4.3	1	5.3	1	3.2
##	312	8.2	1	5.3	1	3.2
##	313	10.0	1	5.3	1	3.2
##	314	11.8	1	5.3	1	3.2
##	315	13.9	1	5.3	1	3.2
11.11	310	10.0	_	0.0	1	0.2

##	316	12.7	1	5.3	1	3.2
##	317	14.5	1	5.3	1	3.2
##	318	9.7	1	5.3	1	3.2
##	319	11.1	1	5.3	1	3.2
##	320	11.6	1	5.3	1	3.2
##	321	8.3	1	5.3	1	3.2
##	322	7.1	1	5.3	1	3.2
##	323	11.3	1	5.3	1	3.2
##	324	12.5	1	5.3	1	3.2
##	325	9.9	1	5.3	1	3.2
##	326	11.8	1	5.3	1	3.2
##	327	13.7	1	5.3	1	3.2
##	328	13.5	1	5.3	1	3.2
##	329	15.8	1	5.3	1	3.2
##	330	13.5	1	5.3	1	3.2
##	331	16.3	1	5.3	1	3.2
##	332	16.5	1	5.3	1	3.2
##	333	12.3	1	5.3	1	3.2
##	334	1.2	1	5.3	2	3.2
##	335	1.4	1	5.3	2	3.2
##	336	2.6	1	5.3	2	3.2
##	337	2.8	1	5.3	2	3.2
##	338	1.0	1	5.3	2	3.2
##	339	0.8	1	5.3	2	3.2
##	340	1.4	1	5.3	2	3.2
##	341	1.0	1	5.3	2	3.2
##	342	1.4	1	5.3	2	3.2
##	343	1.0	1	5.3	2	3.2
##	344	2.2	1	5.3	2	3.2
##	345	1.0	1	5.3	2	3.2
##	346	1.4	1	5.3	2	3.2
##	347	1.6	1	5.3	2	3.2
##	348	2.0	1	5.3	2	3.2
##	349	1.1	1	5.3	2	3.2
##	350	3.7	1	5.3	2	3.2
##	351	2.5	1	5.3	2	3.2
##	352	3.1	1	5.3	2	3.2
##	353	0.6	1	5.3	2	3.2
##	354	1.1	1	5.3	2	3.2
##	355	1.1	1	5.3	2	3.2
##	356	0.6	1	5.3	2	3.2
##	357	0.3	1	5.3	2	3.2
##	358	0.3	1	5.3	2	3.2
##	359	0.8	1	5.3	2	3.2
##	360	1.1	1	5.3	2	3.2
##	361	0.6	1	5.3	2	3.2
##	362	0.6	1		2	3.2
	363			5.3		
##		0.3	1	5.3	2	3.2
##	364	6.2	1	5.3	2	3.2
##	365	4.9	1	5.3	2	3.2
##	366 367	2.4	1	5.3	2	3.2
##	367	1.3	1	5.3	2	3.2
##	368	2.5	1	5.3	2	3.2
##	369	1.6	1	5.3	2	3.2

##	370	2.7	1	5.3	2	3.2
##	371	1.6	1	5.3	2	3.2
##	372	3.3	1	5.3	2	3.2
##	373	1.6	1	5.3	2	3.2
##	374	1.8	1	5.3	2	3.2
##	375	2.5	1	5.3	2	3.2
##	376	0.5	1	5.3	2	3.2
##	377	1.1	1	5.3	2	3.2
##	378	0.5	1	5.3	2	3.2
##	379	1.6	1	5.3	2	3.2
			1	5.3		
##	380	4.7			2	3.2
##	381	5.3	1	5.3	2	3.2
##	382	5.0	1	5.3	2	3.2
##	383	3.1	1	5.3	2	3.2
##	384	2.7	1	5.3	2	3.2
##	385	1.7	1	5.3	2	3.2
##	386	2.5	1	5.3	2	3.2
##	387	2.4	1	5.3	2	3.2
##	388	2.6	1	5.3	2	3.2
##	389	2.3	1	5.3	2	3.2
##	390	2.2	1	5.3	2	3.2
##	391	2.1	1	5.3	2	3.2
##	392	2.4	1	5.3	2	3.2
##	393	2.6	1	5.3	2	3.2
##	394	3.3	1	5.3	2	3.2
##	395	3.0	1	5.3	2	3.2
##	396	3.0	1	5.3	2	3.2
##	397	0.7	1	5.3	2	3.2
##	398	1.9	1	5.3	2	3.2
##	399	2.2	1	5.3	2	3.2
##	400	1.4	1	5.3	2	3.2
##	401	1.2	1	5.3	2	3.2
##	402	1.5	1	5.3	2	3.2
##	403	1.9	1	5.3	2	3.2
##	404	2.4	1	5.3	2	3.2
##	405	6.2	1	5.3	2	3.2
##	406	5.0	1	5.3	2	3.2
##	407	3.8	1	5.3	2	3.2
##	408	1.2	1	5.3	2	3.2
##	409	4.7	1	5.3	2	3.2
##	410	3.5	1	5.3	2	3.2
##	411	1.8	1	5.3	2	3.2
##	412	1.6	1	5.3	2	3.2
##	413	2.1	1	5.3	2	3.2
##	414		1		2	
		1.2		5.3		3.2
##	415	1.4	1	5.3	2	3.2
##	416	1.8	1	5.3	2	3.2
##	417	2.9	1	5.3	2	3.2
##	418	1.8	1	5.3	2	3.2
##	419	8.0	1	5.3	2	3.2
##	420	6.6	1	5.3	2	3.2
##	421	4.5	1	5.3	2	3.2
##	422	5.6	1	5.3	2	3.2
##	423	5.6	1	5.3	2	3.2

##	424	6.3	1	5.3	2	3.2
##	425	5.3	1	5.3	2	3.2
##	426	3.2	1	5.3	2	3.2
##	427	2.9	1	5.3	2	3.2
##	428	12.6	1	5.3	2	3.2
##	429	8.1	1	5.3	2	3.2
##	430	7.4	1	5.3	2	3.2
##	431	8.1	1	5.3	2	3.2
##	432	6.6	1	5.3	2	3.2
##	433	5.0	1	5.3	2	3.2
##	434	6.1	1	5.3	2	3.2
##	435	5.4	1	5.3	2	3.2
##	436	6.4	1	5.3	2	3.2
##	437	6.7	1	5.3	2	3.2
##	438	8.6	1	5.3	2	3.2
##	439	8.9	1	5.3	2	3.2
##	440	7.9	1	5.3	2	3.2
##	441	9.7	1	5.3	2	3.2
##	442	11.0	1	5.3	2	3.2
	443				2	
##	444	11.5	1	5.3		3.2
##		11.0	1	5.3	2	3.2
##	445	3.8	1	5.3	2	3.2
##	446	4.7	1	5.3	2	3.2
##	447	6.4	1	5.3	2	3.2
##	448	3.5	1	5.3	2	3.2
##	449	4.0	1	5.3	2	3.2
##	450	3.3	1	5.3	2	3.2
##	451	2.1	1	5.3	2	3.2
##	452	2.1	1	5.3	2	3.2
##	453	0.9	1	5.3	2	3.2
##	454	7.0	1	5.3	2	3.2
##	455	3.9	1	5.3	2	3.2
##	456	4.1	1	5.3	2	3.2
##	457	6.5	1	5.3	2	3.2
##	458	7.8	1	5.3	2	3.2
##	459	6.9	1	5.3	2	3.2
##	460	6.3	1	5.3	2	3.2
##	461	4.4	1	5.3	2	3.2
##	462	6.1	1	5.3	2	3.2
##	463	3.3	1	5.3	2	3.2
##	464	4.3	1	5.3	2	3.2
##	465	2.4	1	5.3	2	3.2
##	466	2.8	1	5.3	2	3.2
##	467	1.5	1	5.3	2	3.2
##	468	4.3	1	5.3	2	3.2
##	469	3.1	1	5.3	2	3.2
##	470	2.8	1	5.3	2	3.2
##	471	5.1	1	5.3	1	3.2
##	472	4.6	1	5.3	1	3.2
##	473	3.9	1	5.3	1	3.2
##	474	3.4	1	5.3	1	3.2
##	475	3.6	1	5.3	1	3.2
##	476	2.7	1	5.3	1	3.2
##	477	4.0	1	5.3	1	3.2

##	478	4.9	1	5.3	1	3.2
##	479	5.2	1	5.3	1	3.2
##	480	4.9	1	5.3	1	3.2
##	481	5.2	1	5.3	1	3.2
##	482	5.9	1	5.3	1	3.2
##	483	5.4	1	5.3	1	3.2
##	484	4.6	1	5.3	1	3.2
##	485	6.0	1	5.3	1	3.2
##	486	7.3	1	5.3	1	3.2
##	487	5.0	1	5.3	1	3.2
##	488	5.0	1	5.3	1	3.2
##	489	5.8	1	5.3	1	3.2
##	490	4.0	1	5.3	1	3.2
##	491	3.0	1	5.3	1	3.2
##	492	5.0	1	5.3	1	3.2
##	493	7.3	1	5.3	1	3.2
##	494	8.1	1	5.3	1	3.2
##	495	10.3	1	5.3	1	3.2
##	496	12.1	1	5.3	1	3.2
##	497	11.1	1	5.3	1	3.2
##	498	9.1	1	5.3	1	3.2
##	499	11.1	1	5.3	1	3.2
##	500	12.5	1	5.3	1	3.2
##	501	0.5	1	5.3	1	3.2
##	502	1.8	1	5.3	1	3.2
##	503	0.8	1	5.3	1	3.2
##	504	1.8	1	5.3	1	3.2
##	505	2.6	1	5.3	1	3.2
##	506	1.3	1	5.3	1	3.2
##	507	1.3	1	5.3	1	3.2
##	508	1.1	1	5.3	1	3.2
##	509	4.0	1	5.3	1	3.2
##		1.8	1	5.3	1	
	510 511		1		1	3.2
##	512	2.6		5.3		3.2
##		2.4	1	5.3	1 1	3.2
##	513	4.0	1	5.3		3.2
##	514	6.8	1	5.3	1	3.2
##	515	4.3	1	5.3	1	3.2
##	516	4.0	1	5.3	1	3.2
##	517	5.2	1	5.3	1	3.2
##	518	5.2	1	5.3	1	3.2
##	519	8.9	1	5.3	1	3.2
##	520	6.5	1	5.3	1	3.2
##	521	8.3	1	5.3	1	3.2
##	522	8.7	1	5.3	1	3.2
##	523	8.6	1	5.3	1	3.2
##	524	4.0	1	5.3	1	3.2
##	525	4.2	1	5.3	1	3.2
##	526	2.7	1	5.3	1	3.2
##	527	5.0	1	5.3	1	3.2
##	528	5.5	1	5.3	1	3.2
##	529	4.2	1	5.3	1	3.2
##	530	4.8	1	5.3	1	3.2
##	531	5.0	1	5.3	1	3.2

##	532	6.7	1	5.3	1	3.2
##	533	5.7	1	5.3	1	3.2
##	534	5.9	1	5.3	1	3.2
##	535	6.9	1	5.3	1	3.2
##	536	3.8	1	5.3	1	3.2
##	537	4.4	1	5.3	1	3.2
##	538	2.7	1	5.3	1	3.2
##	539	7.0	1	5.3	1	3.2
##	540	10.0	1	5.3	1	3.2
##	541	8.6	1	5.3	1	3.2
##	542	5.5	1	5.3	1	3.2
##	543	11.4	1	5.3	1	3.2
##	544	5.3	1	5.3	1	3.2
##	545	7.5	1	5.3	1	3.2
##	546	10.8	1	5.3	1	3.2
##	547	11.6	1	5.3	1	3.2
##	548	9.1	1	5.3	1	3.2
##	549	7.2	1	5.3	1	3.2
##	550	9.8	1	5.3	1	3.2
##	551	8.7	1	5.3	1	3.2
##	552	11.0	1	5.3	1	3.2
##	553	12.2	1	5.3	1	3.2
##	554	11.8	1	5.3	1	3.2
##	555	12.8	1	5.3	1	3.2
##	556	12.7	1	5.3	1	3.2
##	557	10.4	1	5.3	1	3.2
##	558	12.6	1	5.3	1	3.2
##	559	10.4	1	5.3	1	3.2
##	560	8.4	1	5.3	1	3.2
##	561	7.8	1	5.3	1	3.2
##	562	5.0	1	5.3	1	3.2
##	563	5.8	1	5.3	1	3.2
##	564	6.0	1	5.3	1	3.2
##	565	4.3	1	5.3	1	3.2
##	566	6.2	1	5.3	1	3.2
##	567	7.0	1	5.3	1	3.2
##	568	8.3	1	5.3	1	3.2
##	569	10.5	1	5.3	1	3.2
##	570	9.0	1	5.3	1	3.2
##	571	6.0	1	5.3	1	3.2
##	572	5.6	1	5.3	1	3.2
##	573	4.9	1	5.3	1	3.2
##	574	2.3	1	5.3	1	3.2
##	575	2.6	1	5.3	1	3.2
##	576	1.9	1	5.3	1	3.2
##	577	3.4	1	5.3	1	3.2
##	578	1.9	1	5.3	1	3.2
##	579	1.1	1	5.3	1	3.2
##	580	0.8	1	5.3	1	3.2
##	581	3.0	1	5.3	1	3.2
##	582	3.8	1	5.3	1	3.2
##	583	5.6	1	5.3	1	3.2
##	584	0.7	1	5.3	1	3.2
##	585	0.7	1	5.3	1	3.2
##	505	0.7	1	5.5	1	3.2

##	586	1.1	1	5.3	1	3.2
##	587	1.1	1	5.3	1	3.2
##	588	0.7	1	5.3	1	3.2
##	589	1.1	1	5.3	1	3.2
##	590	6.7	1	5.3	1	3.2
##	591	6.1	1	5.3	1	3.2
##	592	8.0	1	5.3	1	3.2
##	593	8.3	1	5.3	1	3.2
##	594	5.8	1	5.3	1	3.2
##	595	4.8	1	5.3	1	3.2
##	596	2.9	1	5.3	1	3.2
##	597	2.7	1	5.3	1	3.2
			1		1	
##	598	2.7		5.3		3.2
##	599	3.0	1	5.3	1	3.2
##	600	3.8	1	5.3	1	3.2
##	601	3.8	1	5.3	1	3.2
##	602	3.5	1	5.3	1	3.2
##	603	3.2	1	5.3	1	3.2
##	604	3.8	1	5.3	1	3.2
##	605	5.1	1	5.3	1	3.2
##	606	8.2	1	5.3	1	3.2
##	607	3.0	1	5.3	1	3.2
##	608	1.8	1	5.3	1	3.2
##	609	1.8	1	5.3	1	3.2
##	610	1.6	1	5.3	1	3.2
##	611	1.1	1	5.3	1	3.2
##	612	1.8	1	5.3	1	3.2
##	613	0.7	1	5.3	1	3.2
##	614	0.8	1	5.3	1	3.2
##	615	1.4	1	5.3	1	3.2
##	616	1.4	1	5.3	1	3.2
##	617	1.3	1	5.3	1	3.2
##	618	1.3	1	5.3	1	3.2
##	619	2.5	1	5.3	1	3.2
##	620	3.3	1	5.3	1	3.2
##	621	3.0	1	5.3	1	3.2
##	622	2.1	1	5.3	1	3.2
##			1		1	
##	623 624	4.2		5.3 5.3	1	3.2
		2.6	1			
##	625	2.5	1	5.3	1	3.2
##	626	2.8	1	5.3	1	3.2
##	627	2.8	1	5.3	1	3.2
##	628	6.4	1	5.3	1	3.2
##	629	5.6	1	5.3	1	3.2
##	630	6.2	1	5.3	1	3.2
##	631	4.0	1	5.3	1	3.2
##	632	3.2	1	5.3	1	3.2
##	633	2.3	1	5.3	1	3.2
##	634	2.7	1	5.3	1	3.2
##	635	5.9	1	5.3	1	3.2
##	636	4.8	1	5.3	1	3.2
##	637	6.3	1	5.3	1	3.2
##	638	4.4	1	5.3	1	3.2
##	639	4.4	1	5.3	1	3.2

##	640	3.7	1	5.3	1	3.2
##	641	2.1	1	5.3	1	3.2
##	642	3.0	1	5.3	1	3.2
##	643	1.6	1	5.3	1	3.2
##	644	4.0	1	5.3	1	3.2
##	645	3.7	1	5.3	1	3.2
##	646	2.5	1	5.3	1	3.2
##	647	4.1	1	5.3	1	3.2
##	648	3.7	1	5.3	1	3.2
##	649	3.8	1	5.3	1	3.2
##	650	4.8	1	5.3	1	3.2
##	651	4.2	1	5.3	1	3.2
##	652	2.5	1	5.3	1	3.2
##	653	8.2	1	5.3	1	3.2
##	654	8.9	1	5.3	1	3.2
##	655	2.8	1	5.3	1	3.2
##	656	4.3	1	5.3	1	3.2
##	657	7.4	1	5.3	1	3.2
##	658	6.1	1	5.3	1	3.2
##	659	4.8	1	5.3	1	3.2
##	660	7.4	1	5.3	1	3.2
##	661	5.4	1	5.3	1	3.2
##	662	3.8	1	5.3	1	3.2
##	663	2.1	1	5.3	2	3.2
##	664	0.5	1	5.3	2	3.2
##	665	0.2	1	5.3	2	3.2
##	666	0.1	1	5.3	2	3.2
##	667	0.5	1	5.3	2	3.2
##	668	0.2	1	5.3	2	3.2
##	669	0.1	1	5.3	2	3.2
##	670	4.4	1	5.3	1	3.2
##	671	3.4	1	5.3	1	3.2
##	672	5.0	1	5.3	1	3.2
##	673	4.1	1	5.3	1	3.2
##	674	7.9	1	5.3	1	3.2
##	675	6.9	1	5.3	1	3.2
##	676	6.4	1	5.3	1	3.2
##	677	9.7	1	5.3	1	3.2