

# HW05.Rmd

*Shashi*

*February 12, 2018*

I have executed these exercises on my own and written the answers in my own words. Signed: Shashi Shankar

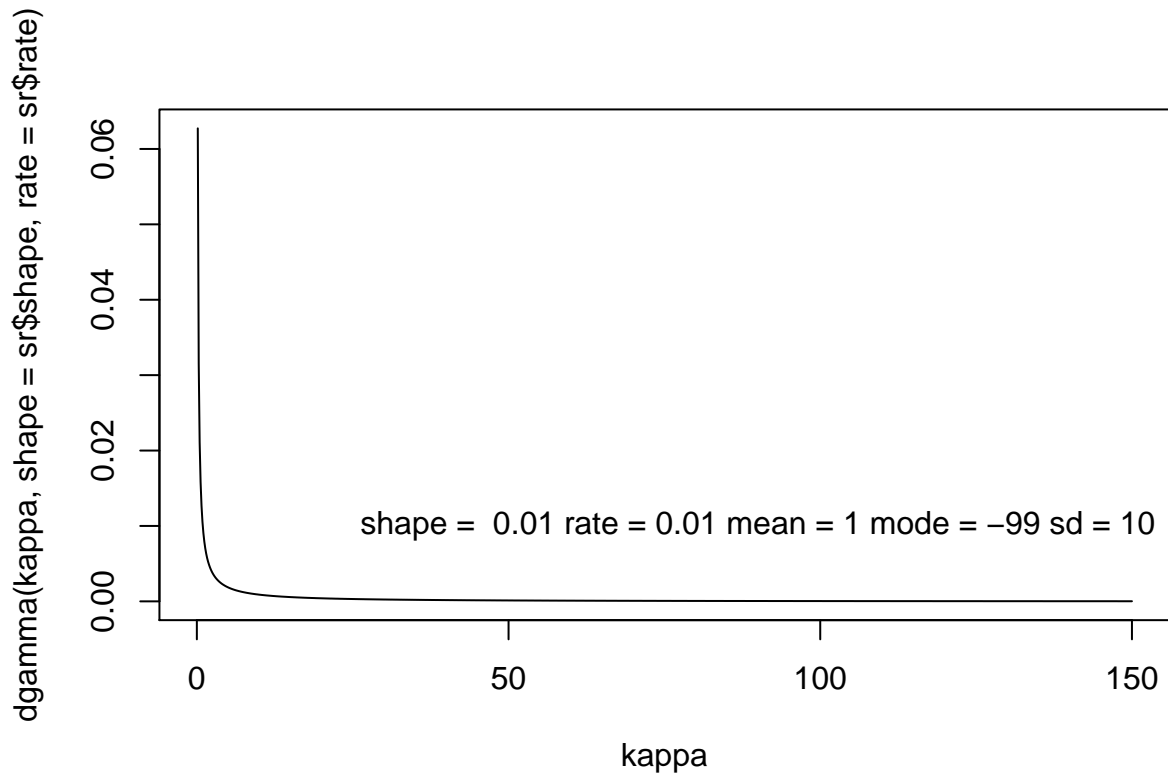
1.

```
kappa = seq( 0 , 150 , length=1001 )
source("DBDA2E-utilities.R")

##
## *****
## Kruschke, J. K. (2015). Doing Bayesian Data Analysis, Second Edition:
## A Tutorial with R, JAGS, and Stan. Academic Press / Elsevier.
## *****

## Loading required package: coda
## Linked to JAGS 4.2.0
## Loaded modules: basemod,bugs

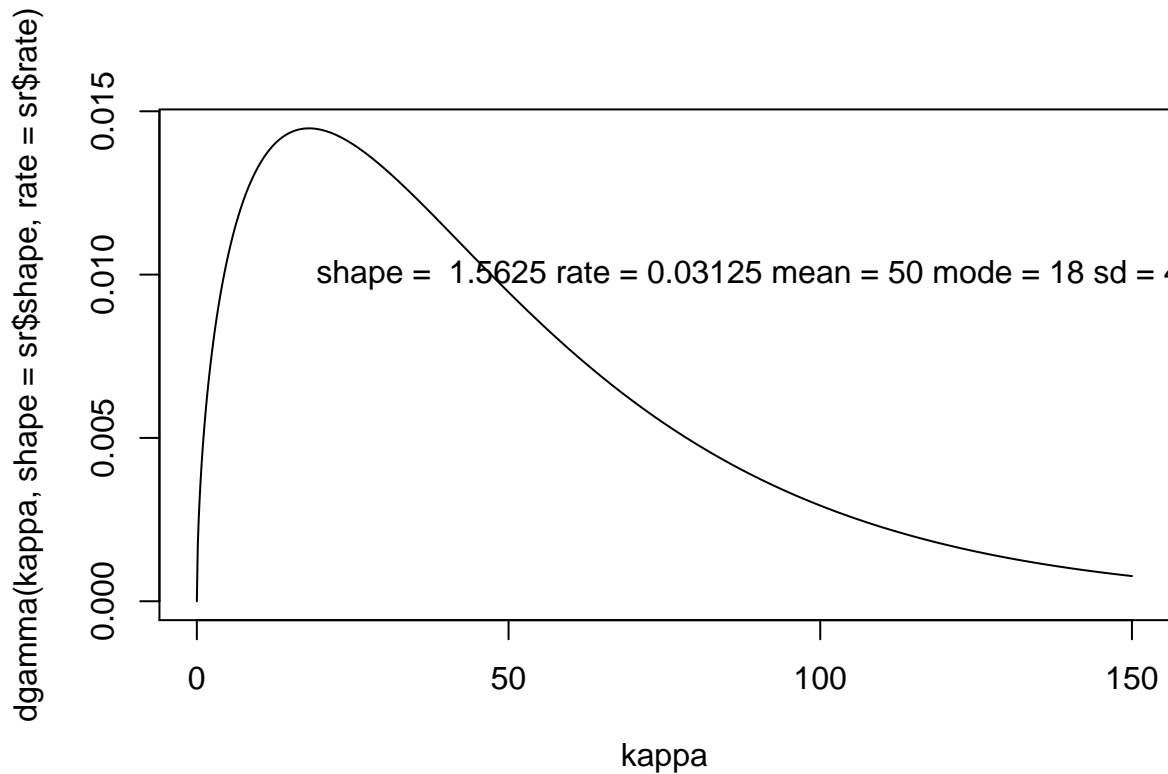
mean <- 1
sd <- 10
sr = gammaShRaFromMeanSD( mean=1 , sd=10 )
mode = (sr$shape - 1)/sr$rate
plot( kappa , dgamma( kappa , shape=sr$shape , rate=sr$rate ) , type="l")
text(90,0.01, paste("shape = ", toString(sr$shape) , "rate =", toString(sr$rate), "mean =", toString(me
```



```
kappa = seq( 0 , 150 , length=1001 )
source("DBDA2E-utilities.R")

##
## *****
## Kruschke, J. K. (2015). Doing Bayesian Data Analysis, Second Edition:
## A Tutorial with R, JAGS, and Stan. Academic Press / Elsevier.
## *****

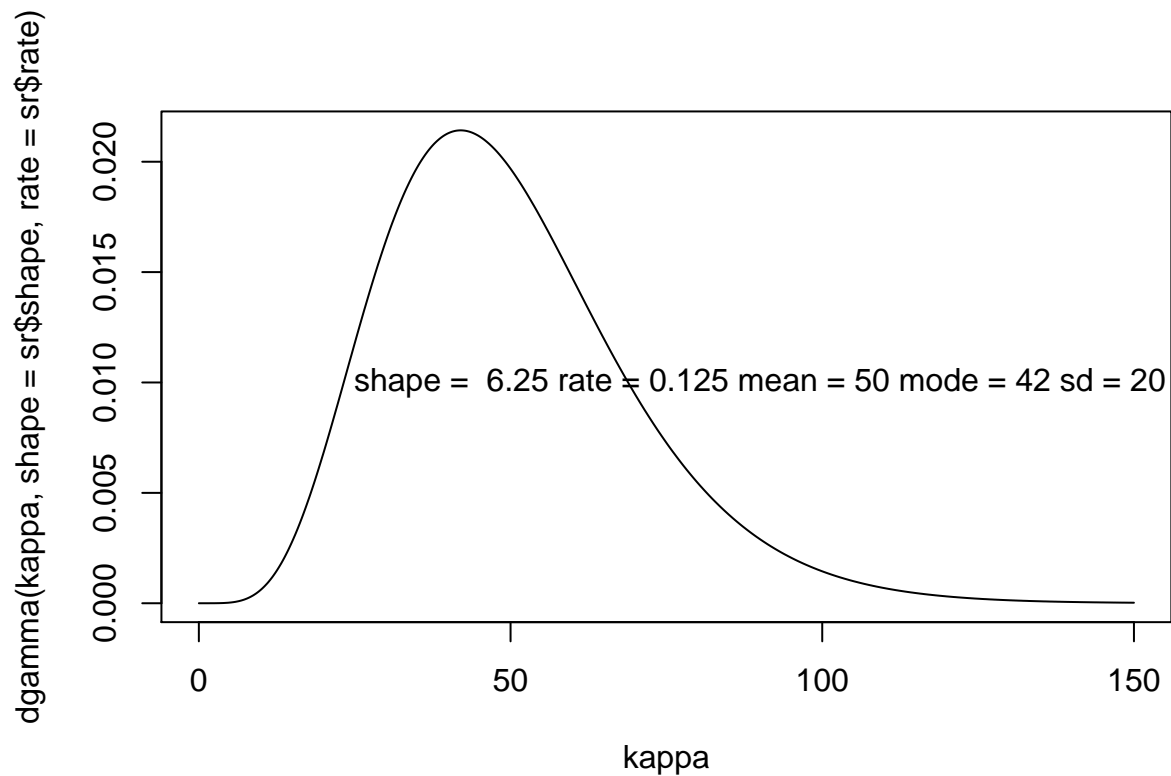
mode <- 18
sd <- 40
sr = gammaShRaFromModeSD( mode=18 , sd=40 )
mean = sr$shape/sr$rate
plot( kappa , dgamma( kappa , shape=sr$shape , rate=sr$rate ) , type="l")
text(90,0.01, paste("shape = ", toString(sr$shape) , "rate =", toString(sr$rate), "mean =", toString(me
```



```
kappa = seq( 0 , 150 , length=1001 )
source("DBDA2E-utilities.R")

##
## *****
## Kruschke, J. K. (2015). Doing Bayesian Data Analysis, Second Edition:
## A Tutorial with R, JAGS, and Stan. Academic Press / Elsevier.
## *****

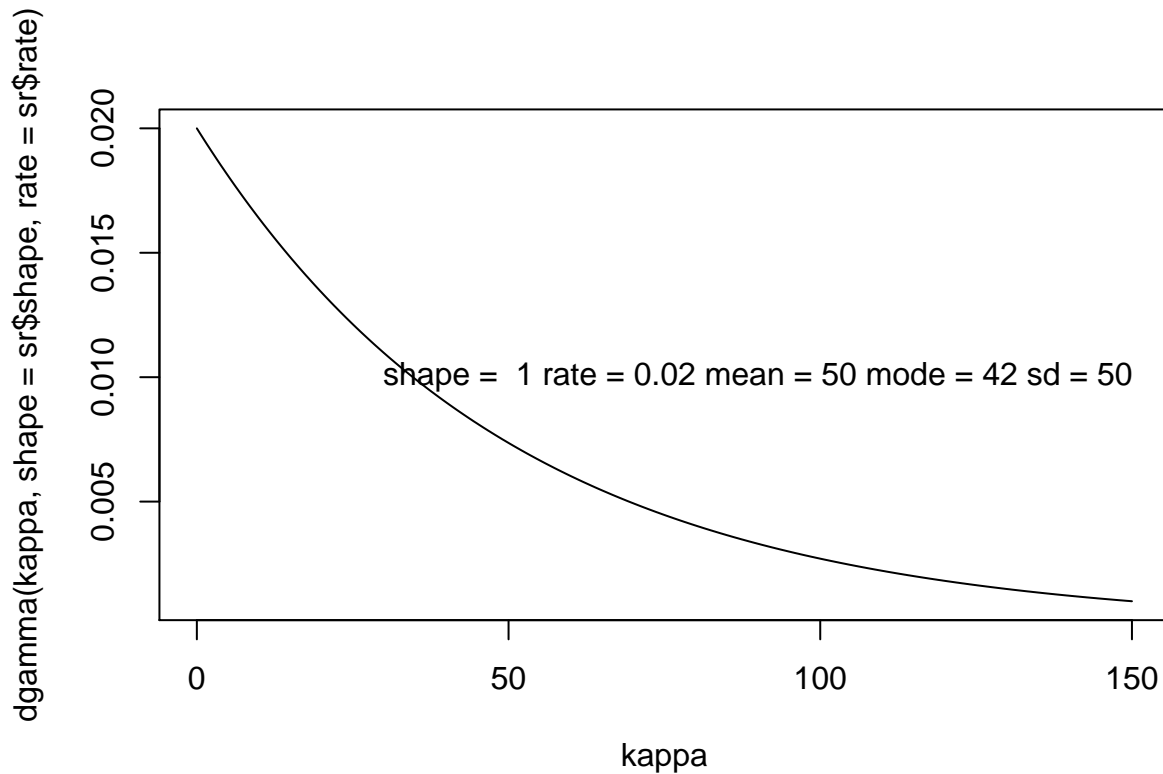
mode <- 42
sd <- 20
sr = gammaShRaFromModeSD( mode=42 , sd=20 )
mean = sr$shape/sr$rate
plot( kappa , dgamma( kappa , shape=sr$shape , rate=sr$rate ) , type="l")
text(90,0.01, paste("shape = ", toString(sr$shape) , "rate =", toString(sr$rate), "mean =", toString(me
```



```
kappa = seq( 0 , 150 , length=1001 )
source("DBDA2E-utilities.R")

##
## *****
## Kruschke, J. K. (2015). Doing Bayesian Data Analysis, Second Edition:
## A Tutorial with R, JAGS, and Stan. Academic Press / Elsevier.
## *****

mean <- 50
sd <- 50
mode = (sr$shape - 1)/sr$rate
sr = gammaShRaFromMeanSD( mean=50 , sd=50 )
mean = sr$shape/sr$rate
plot( kappa , dgamma( kappa , shape=sr$shape , rate=sr$rate ) , type="l")
text(90,0.01, paste("shape = ", toString(sr$shape) , "rate =", toString(sr$rate), "mean =", toString(me
```



2A. Proportion of head for coins 1,2,3 and 4 are 0.25, 0.50, 0.50, and 0.75 respectively.

2B.

```
s = c( 1,1,1,1, 2,2,2,2, 3,3,3,3, 4,4,4,4 ) # subject indicator for each datum
y = c( 1,0,0,0, 1,1,0,0, 1,1,0,0, 1,1,1,0 ) # value of each datum
theta = c( 0.25 , 0.50 , 0.50 , 0.75 )
omega = 0.5
kappa = 2.0
# lik (below) is likelihood.
lik = 1.0 # initialize
for ( sIdx in unique(s) ) {
  # To understand the next line, unpack it from the inside out. Consider the first
  # time through the for loop, when sIdx is 1. What is s==sIdx? What is y[s==sIdx]?
  # What is theta[sIdx]? What is theta[sIdx]^y[s==sIdx]? etc.
  # What is this line computing in Eqn 9.10?
  lik = lik * prod( theta[sIdx]^y[s==sIdx] * (1-theta[sIdx])^(1-y[s==sIdx]) )
}
a = omega*(kappa-2)+1
b = (1-omega)*(kappa-2)+1
# What is the next line computing in Eqn 9.10?
lik = lik * prod( theta^(a-1) * (1-theta)^(b-1) / beta(a,b) )
```

```
show(lik)
```

```
## [1] 4.345179e-05
```

Shape of the Beta distribution is flat. These parameter values do not constitute any reasonable shrinkage relative to the data proportions.

## 2C.

```
s = c( 1,1,1,1, 2,2,2,2, 3,3,3,3, 4,4,4,4 ) # subject indicator for each datum
y = c( 1,0,0,0, 1,1,0,0, 1,1,0,0, 1,1,1,0 ) # value of each datum
theta = c( 0.35 , 0.50 , 0.50 , 0.65 )
omega = 0.5
kappa = 20.0
# lik (below) is likelihood.
lik = 1.0 # initialize
for ( sIdx in unique(s) ) {
  # To understand the next line, unpack it from the inside out. Consider the first
  # time through the for loop, when sIdx is 1. What is s==sIdx? What is y[s==sIdx]?
  # What is theta[sIdx]? What is theta[sIdx]^y[s==sIdx]? etc.
  # What is this line computing in Eqn 9.10?
  lik = lik * prod( theta[sIdx]^y[s==sIdx] * (1-theta[sIdx])^(1-y[s==sIdx]) )
}
a = omega*(kappa-2)+1
b = (1-omega)*(kappa-2)+1
# What is the next line computing in Eqn 9.10?
lik = lik * prod( theta^(a-1) * (1-theta)^(b-1) / beta(a,b) )

show(lik)
```

```
## [1] 0.001019145
```

Shape of the Beta distribution is peaked. Parameter values in part c yield a higher likelihood value for the data. When kappa is larger, the individual theta values must be shrunk more.

## 3.

```
source("Jags-Ydich-XnomSsubj-MbinomBetaOmegaKappa-Example.R")

##
## *****
## Kruschke, J. K. (2015). Doing Bayesian Data Analysis, Second Edition:
## A Tutorial with R, JAGS, and Stan. Academic Press / Elsevier.
## *****
##
## Calling 3 simulations using the parallel method...
## Following the progress of chain 1 (the program will wait for all
## chains to finish before continuing):
## Welcome to JAGS 4.2.0 on Tue Feb 13 01:36:22 2018
## JAGS is free software and comes with ABSOLUTELY NO WARRANTY
## Loading module: basemod: ok
## Loading module: bugs: ok
## . . Reading data file data.txt
```

```

## . Compiling model graph
##   Resolving undeclared variables
##   Allocating nodes
## Graph information:
##   Observed stochastic nodes: 28
##   Unobserved stochastic nodes: 30
##   Total graph size: 239
## . Reading parameter file inits1.txt
## . Initializing model
## . Adapting 500
## -----| 500
## ++++++ 100%
## Adaptation successful
## . Updating 500
## -----| 500
## ***** 100%
## . . . . Updating 66670
## -----| 66650
## ***** 100%
## * 100%
## . . . . Updating 0
## . Deleting model
## .
## All chains have finished
## Simulation complete. Reading coda files...
## Coda files loaded successfully
## Finished running the simulation
##   user  system elapsed
##   2.22    0.37   16.39

##               Mean      Median      Mode      ESS HDImass
## omega          0.43660840 0.436380 0.43459396 11587.7    0.95
## kappa          59.07611672 59.444100 80.41875967 13404.0    0.95
## theta[1]        0.38148434 0.385305 0.39470797 15800.1    0.95
## theta[2]        0.39896354 0.401982 0.41215184 17136.6    0.95
## theta[3]        0.41539481 0.416082 0.42406655 17312.7    0.95
## theta[4]        0.41536504 0.415837 0.41703893 16624.8    0.95
## theta[5]        0.41578363 0.416448 0.41181900 17437.3    0.95
## theta[6]        0.41535949 0.416176 0.42448668 17253.2    0.95
## theta[7]        0.41530822 0.416820 0.42244144 17881.6    0.95
## theta[8]        0.41535402 0.416834 0.42391393 17155.7    0.95
## theta[9]        0.41488253 0.415588 0.40758333 18005.4    0.95
## theta[10]       0.41573415 0.416430 0.41818729 17290.9    0.95
## theta[11]       0.43250689 0.432355 0.43549793 17927.2    0.95
## theta[12]       0.43253952 0.432688 0.44393362 18332.3    0.95
## theta[13]       0.43315474 0.432744 0.42064925 17828.2    0.95
## theta[14]       0.43318550 0.432510 0.42437922 17953.9    0.95
## theta[15]       0.43246072 0.432140 0.43435353 17741.8    0.95
## theta[16]       0.44985881 0.447718 0.43844311 17369.4    0.95
## theta[17]       0.44970940 0.447768 0.44289418 17583.6    0.95
## theta[18]       0.45061039 0.449043 0.45189460 17487.8    0.95
## theta[19]       0.45042418 0.448944 0.45144929 19746.3    0.95
## theta[20]       0.45081402 0.449629 0.44867291 17573.2    0.95
## theta[21]       0.44982469 0.449013 0.45091455 18031.8    0.95

```

## theta[22]	0.45042511	0.449347	0.44890458	18519.1	0.95
## theta[23]	0.46690268	0.464260	0.46603992	18087.2	0.95
## theta[24]	0.46766484	0.465409	0.45650759	18254.3	0.95
## theta[25]	0.48533028	0.481407	0.48133251	17979.2	0.95
## theta[26]	0.48408701	0.480356	0.47647378	16523.1	0.95
## theta[27]	0.48457453	0.480538	0.47572360	16608.2	0.95
## theta[28]	0.50208917	0.496958	0.48583313	17281.3	0.95
## theta[1]-theta[14]	-0.05170116	-0.047566	-0.03442738	18952.1	0.95
## theta[1]-theta[28]	-0.12060483	-0.109148	-0.09917428	16000.5	0.95
## theta[14]-theta[28]	-0.06890367	-0.063555	-0.06072951	18512.8	0.95
##	HDIlow	HDIhigh	CompVal	PcntGtCompVal	ROPElow
## omega	0.369849	0.503041	0.5	3.109845	NA
## kappa	18.482500	101.983000	NA	NA	NA
## theta[1]	0.235743	0.525622	0.5	4.384781	NA
## theta[2]	0.251855	0.536004	0.5	7.149643	NA
## theta[3]	0.272302	0.553474	0.5	10.999450	NA
## theta[4]	0.278479	0.552419	0.5	10.954452	NA
## theta[5]	0.275141	0.553344	0.5	11.024449	NA
## theta[6]	0.275404	0.550042	0.5	10.639468	NA
## theta[7]	0.278628	0.552679	0.5	10.549473	NA
## theta[8]	0.273096	0.551658	0.5	10.899455	NA
## theta[9]	0.278072	0.553095	0.5	10.744463	NA
## theta[10]	0.278645	0.556353	0.5	10.819459	NA
## theta[11]	0.299250	0.571053	0.5	16.004200	NA
## theta[12]	0.296856	0.571987	0.5	16.124194	NA
## theta[13]	0.298030	0.571797	0.5	16.374181	NA
## theta[14]	0.290858	0.567833	0.5	16.219189	NA
## theta[15]	0.291946	0.563511	0.5	15.984201	NA
## theta[16]	0.308512	0.586395	0.5	22.893855	NA
## theta[17]	0.313390	0.593095	0.5	22.653867	NA
## theta[18]	0.314472	0.591046	0.5	22.843858	NA
## theta[19]	0.314153	0.589374	0.5	22.718864	NA
## theta[20]	0.315483	0.593166	0.5	22.978851	NA
## theta[21]	0.305700	0.585342	0.5	22.603870	NA
## theta[22]	0.318945	0.594191	0.5	23.113844	NA
## theta[23]	0.332766	0.614458	0.5	30.288486	NA
## theta[24]	0.327795	0.609069	0.5	31.213439	NA
## theta[25]	0.346004	0.636755	0.5	39.513024	NA
## theta[26]	0.342017	0.631945	0.5	39.093045	NA
## theta[27]	0.341872	0.629361	0.5	39.483026	NA
## theta[28]	0.357385	0.655331	0.5	48.422579	NA
## theta[1]-theta[14]	-0.240068	0.128246	0.0	28.768562	NA
## theta[1]-theta[28]	-0.340845	0.079730	0.0	10.919454	NA
## theta[14]-theta[28]	-0.268782	0.118653	0.0	23.838808	NA
##	ROPEhigh	PcntLtROPE	PcntInROPE	PcntGtROPE	
## omega	NA	NA	NA	NA	
## kappa	NA	NA	NA	NA	
## theta[1]	NA	NA	NA	NA	
## theta[2]	NA	NA	NA	NA	
## theta[3]	NA	NA	NA	NA	
## theta[4]	NA	NA	NA	NA	
## theta[5]	NA	NA	NA	NA	
## theta[6]	NA	NA	NA	NA	
## theta[7]	NA	NA	NA	NA	



```
## theta[8] NA NA NA NA
## theta[9] NA NA NA NA
## theta[10] NA NA NA NA
## theta[11] NA NA NA NA
## theta[12] NA NA NA NA
## theta[13] NA NA NA NA
## theta[14] NA NA NA NA
## theta[15] NA NA NA NA
## theta[16] NA NA NA NA
## theta[17] NA NA NA NA
## theta[18] NA NA NA NA
## theta[19] NA NA NA NA
## theta[20] NA NA NA NA
## theta[21] NA NA NA NA
## theta[22] NA NA NA NA
## theta[23] NA NA NA NA
## theta[24] NA NA NA NA
## theta[25] NA NA NA NA
## theta[26] NA NA NA NA
## theta[27] NA NA NA NA
## theta[28] NA NA NA NA
## theta[1]-theta[14] NA NA NA NA
## theta[1]-theta[28] NA NA NA NA
## theta[14]-theta[28] NA NA NA NA
```

Note that the `echo = FALSE` parameter was added to the code chunk to prevent printing of the R code that generated the plot.

```
##
## *****
## Kruschke, J. K. (2015). Doing Bayesian Data Analysis, Second Edition:
## A Tutorial with R, JAGS, and Stan. Academic Press / Elsevier.
## *****
##
## Calling 3 simulations using the parallel method...
## Following the progress of chain 1 (the program will wait for all
## chains to finish before continuing):
## Welcome to JAGS 4.2.0 on Tue Feb 13 01:36:44 2018
## JAGS is free software and comes with ABSOLUTELY NO WARRANTY
## Loading module: basemod: ok
## Loading module: bugs: ok
## . . Reading data file data.txt
## . Compiling model graph
##   Resolving undeclared variables
##   Allocating nodes
## Graph information:
##   Observed stochastic nodes: 28
##   Unobserved stochastic nodes: 30
##   Total graph size: 239
## . Reading parameter file inits1.txt
## . Initializing model
## . Adapting 500
## -----| 500
## ++++++ 100%
## Adaptation successful
```

```

## . Updating 500
## -----| 500
## ***** 100%
## . . . . Updating 66670
## -----| 66650
## ***** 100%
## * 100%
## . . . . Updating 0
## . Deleting model
## .
## All chains have finished
## Simulation complete. Reading coda files...
## Coda files loaded successfully
## Finished running the simulation
##   user  system elapsed
##   2.42    0.40   16.99

##               Mean      Median      Mode      ESS HDImass
## omega          0.43647149  0.436175  0.42838190 11705.7    0.95
## kappa          59.30915080 59.823400 70.31079120 13016.0    0.95
## theta[1]        0.38172868  0.385122  0.40009817 15486.0    0.95
## theta[2]        0.39862481  0.400254  0.39917720 17280.0    0.95
## theta[3]        0.41505286  0.416094  0.41587651 16880.7    0.95
## theta[4]        0.41510323  0.416215  0.41964837 17207.6    0.95
## theta[5]        0.41659906  0.417517  0.41799460 17027.4    0.95
## theta[6]        0.41549619  0.416412  0.41566942 17273.8    0.95
## theta[7]        0.41490076  0.415424  0.40869516 17518.0    0.95
## theta[8]        0.41523064  0.415570  0.41347395 17739.7    0.95
## theta[9]        0.41520088  0.416113  0.41817136 17549.8    0.95
## theta[10]       0.41527636  0.416564  0.42124799 17060.0    0.95
## theta[11]       0.43254703  0.432215  0.43275464 18723.4    0.95
## theta[12]       0.43258245  0.432030  0.42716137 17631.0    0.95
## theta[13]       0.43280004  0.432931  0.43682610 18028.3    0.95
## theta[14]       0.43219157  0.431819  0.43099541 18160.7    0.95
## theta[15]       0.43247645  0.432291  0.42118123 17902.0    0.95
## theta[16]       0.44949060  0.447893  0.44208295 18401.3    0.95
## theta[17]       0.44941191  0.447792  0.45249395 18107.8    0.95
## theta[18]       0.44899151  0.447771  0.44731743 17891.9    0.95
## theta[19]       0.44994844  0.448411  0.44976714 17759.1    0.95
## theta[20]       0.45005678  0.448921  0.44866029 18318.2    0.95
## theta[21]       0.44917645  0.447849  0.44632361 17891.7    0.95
## theta[22]       0.45016305  0.448545  0.45216555 17165.3    0.95
## theta[23]       0.46710639  0.464921  0.46674077 16408.6    0.95
## theta[24]       0.46724183  0.464841  0.45863540 17562.0    0.95
## theta[25]       0.48353287  0.480394  0.47531948 17982.6    0.95
## theta[26]       0.48383578  0.479999  0.47754342 16498.6    0.95
## theta[27]       0.48475702  0.480645  0.47552334 14680.9    0.95
## theta[28]       0.50088674  0.496279  0.49251653 15807.1    0.95
## theta[1]-theta[14] -0.05046289 -0.046289 -0.04205044 18282.8    0.95
## theta[1]-theta[28] -0.11915806 -0.107616 -0.09273484 15932.4    0.95
## theta[14]-theta[28] -0.06869517 -0.063413 -0.06609809 18703.1    0.95
##               HDIlow  HDIhigh CompVal PcntGtCompVal ROPElow
## omega          0.368410  0.501242      0.5      3.034848      NA
## kappa          18.793400 101.987000      NA      NA      NA

```

## theta[1]	0.231524	0.521920	0.5	4.399780	NA
## theta[2]	0.264161	0.543366	0.5	6.984651	NA
## theta[3]	0.278754	0.554263	0.5	10.624469	NA
## theta[4]	0.279996	0.552325	0.5	10.709465	NA
## theta[5]	0.278945	0.555243	0.5	11.014449	NA
## theta[6]	0.278057	0.552066	0.5	10.489476	NA
## theta[7]	0.270254	0.547852	0.5	10.724464	NA
## theta[8]	0.277790	0.553066	0.5	10.964452	NA
## theta[9]	0.275194	0.551057	0.5	11.229439	NA
## theta[10]	0.276659	0.553613	0.5	10.464477	NA
## theta[11]	0.298920	0.569920	0.5	16.004200	NA
## theta[12]	0.301434	0.573782	0.5	15.824209	NA
## theta[13]	0.290636	0.564068	0.5	16.074196	NA
## theta[14]	0.294858	0.571150	0.5	16.004200	NA
## theta[15]	0.293537	0.565784	0.5	16.004200	NA
## theta[16]	0.310793	0.586480	0.5	22.648868	NA
## theta[17]	0.314163	0.590247	0.5	22.278886	NA
## theta[18]	0.313117	0.585760	0.5	22.323884	NA
## theta[19]	0.313779	0.586682	0.5	22.553872	NA
## theta[20]	0.313943	0.587254	0.5	23.133843	NA
## theta[21]	0.314855	0.593303	0.5	22.658867	NA
## theta[22]	0.315924	0.587975	0.5	22.983851	NA
## theta[23]	0.332847	0.614177	0.5	30.408480	NA
## theta[24]	0.331132	0.613377	0.5	30.183491	NA
## theta[25]	0.342634	0.628432	0.5	39.228039	NA
## theta[26]	0.340756	0.629268	0.5	38.748063	NA
## theta[27]	0.344705	0.634520	0.5	39.123044	NA
## theta[28]	0.357809	0.653018	0.5	47.842608	NA
## theta[1]-theta[14]	-0.237396	0.133909	0.0	29.598520	NA
## theta[1]-theta[28]	-0.342661	0.075301	0.0	11.059447	NA
## theta[14]-theta[28]	-0.263021	0.121706	0.0	23.628819	NA
##	ROPEhigh	PcntLtROPE	PcntInROPE	PcntGtROPE	
## omega	NA	NA	NA	NA	
## kappa	NA	NA	NA	NA	
## theta[1]	NA	NA	NA	NA	
## theta[2]	NA	NA	NA	NA	
## theta[3]	NA	NA	NA	NA	
## theta[4]	NA	NA	NA	NA	
## theta[5]	NA	NA	NA	NA	
## theta[6]	NA	NA	NA	NA	
## theta[7]	NA	NA	NA	NA	
## theta[8]	NA	NA	NA	NA	
## theta[9]	NA	NA	NA	NA	
## theta[10]	NA	NA	NA	NA	
## theta[11]	NA	NA	NA	NA	
## theta[12]	NA	NA	NA	NA	
## theta[13]	NA	NA	NA	NA	
## theta[14]	NA	NA	NA	NA	
## theta[15]	NA	NA	NA	NA	
## theta[16]	NA	NA	NA	NA	
## theta[17]	NA	NA	NA	NA	
## theta[18]	NA	NA	NA	NA	
## theta[19]	NA	NA	NA	NA	
## theta[20]	NA	NA	NA	NA	

mode = 2.17

95% HDI  
2.25

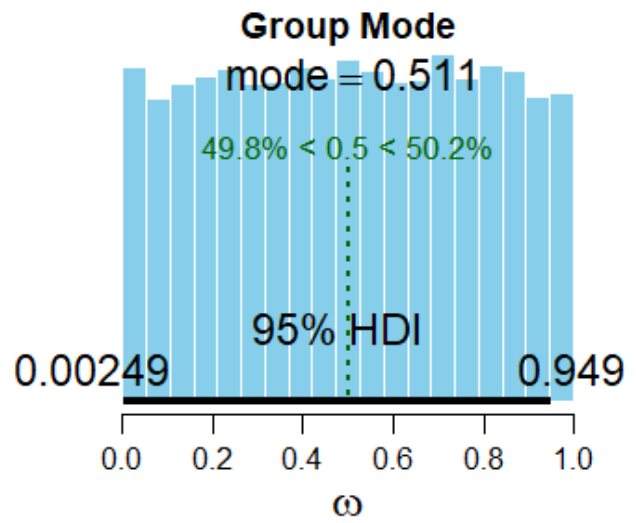
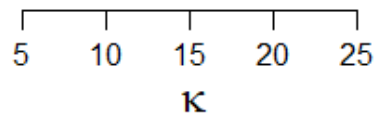
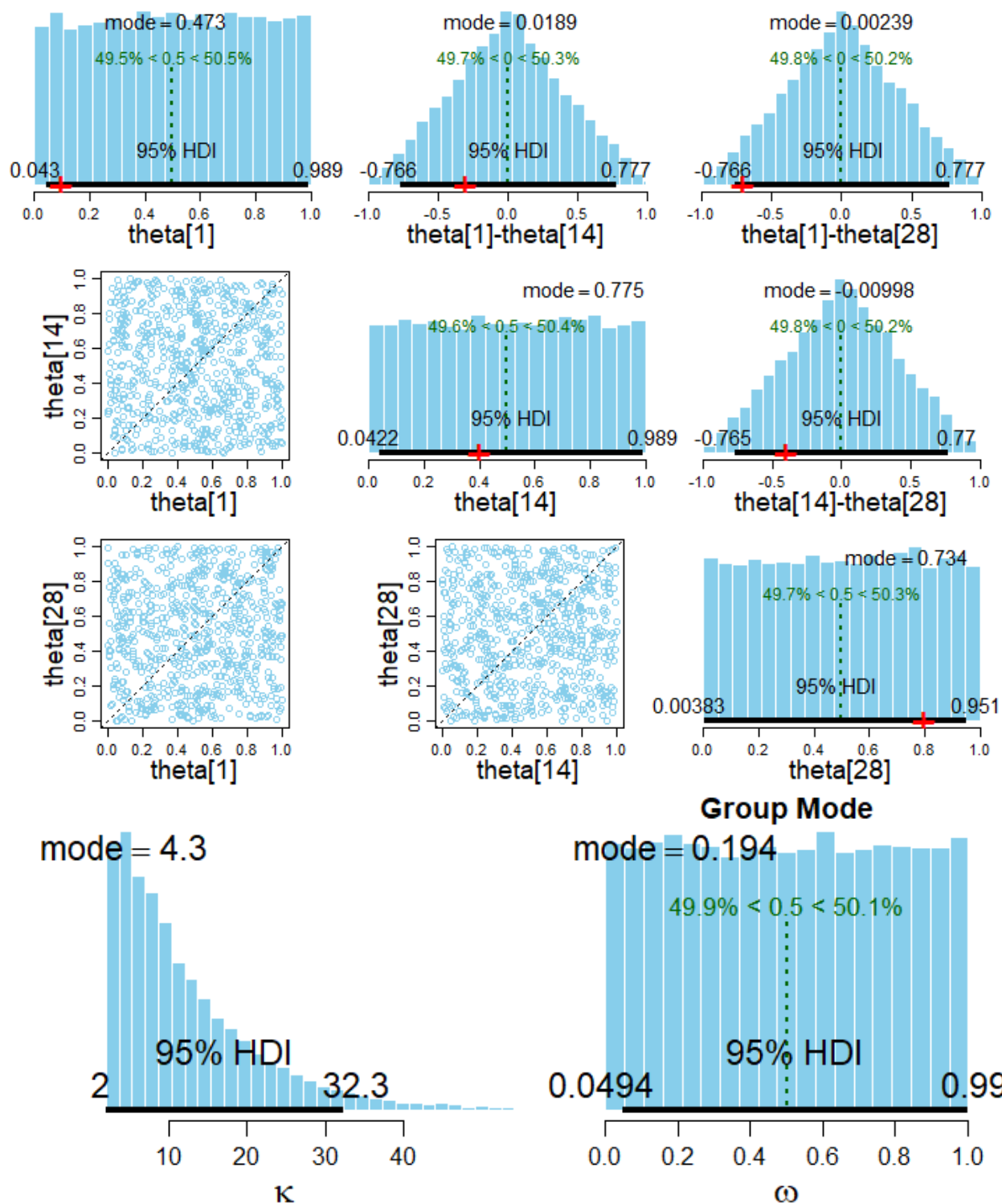
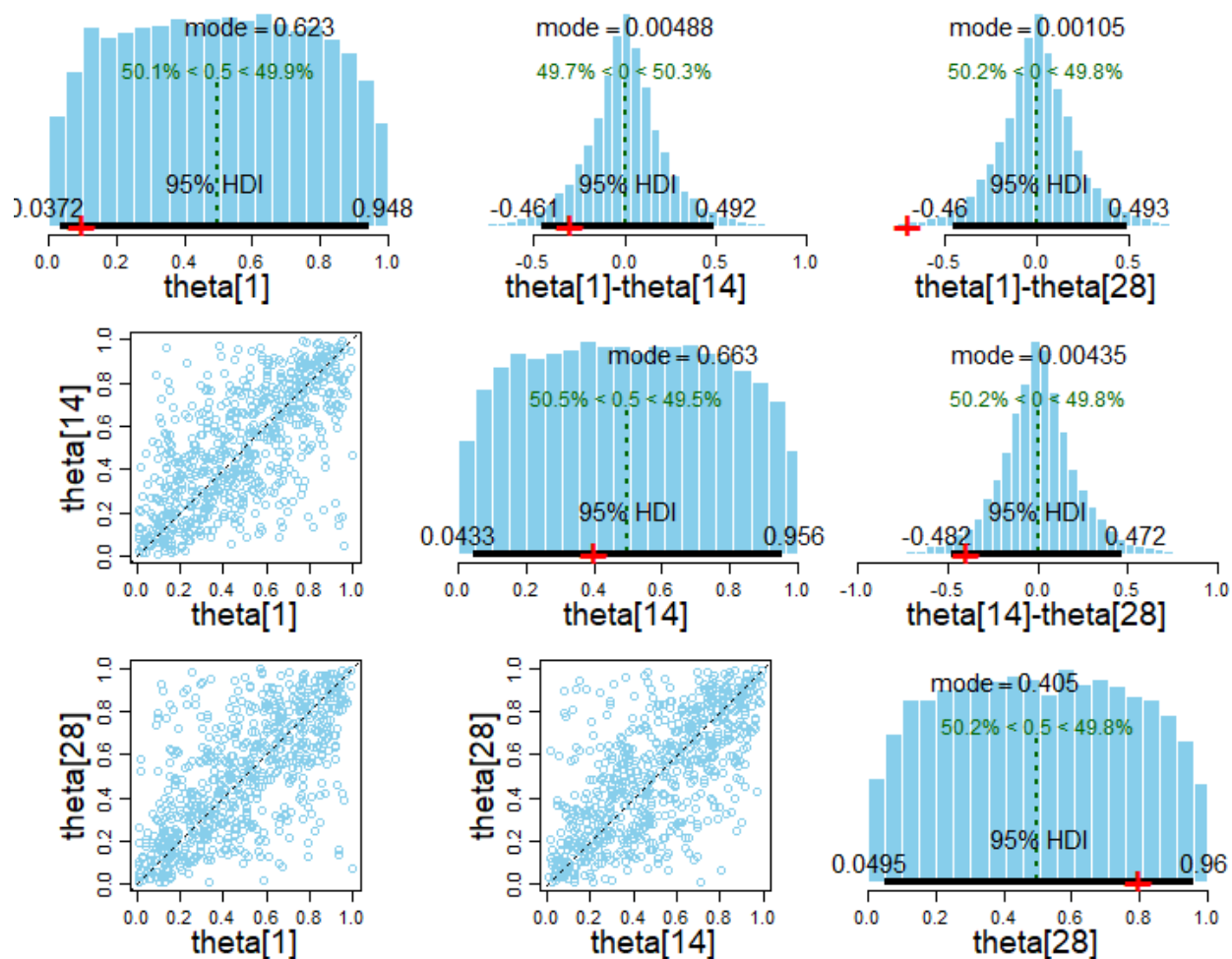


Figure 1:

## theta[21]	NA	NA	NA	NA
## theta[22]	NA	NA	NA	NA
## theta[23]	NA	NA	NA	NA
## theta[24]	NA	NA	NA	NA
## theta[25]	NA	NA	NA	NA
## theta[26]	NA	NA	NA	NA
## theta[27]	NA	NA	NA	NA
## theta[28]	NA	NA	NA	NA
## theta[1]-theta[14]	NA	NA	NA	NA
## theta[1]-theta[28]	NA	NA	NA	NA
## theta[14]-theta[28]	NA	NA	NA	NA





kappa does not get too small When the prior has mode=1. But when the prior has mean=1, kappa has a very high probability of being very small. The two different thetas can have opposite extremes when kappa is very small in the case where prior has mean = 1.

3B. I think the prior with mean=1 is more appropriate as it sets uniform prior for the individual thetas and sets a broad prior on the differences of thetas.

4.

```
# Generate the data frame:
# N.B.: The functions below expect the data to be a data frame,
# with one component being a vector of integer 0,1 values,
# and one component being a factor of subject identifiers.
headsTails = c( rep(1,30),rep(0,100-30),
  rep(1,40),rep(0,100-40),
  rep(1,50),rep(0,100-50),
  rep(1,60),rep(0,100-60),
  rep(1,70),rep(0,100-70) )
subjID = factor( c( rep("A",100),
  rep("B",100),
```

```

rep("C",100),
rep("D",100),
rep("E",100) ) )
myData = data.frame( y=headsTails , s=subjID )
#-----
# Load the relevant model into R's working memory:
source("Jags-Ydich-XnomSsubj-MbernBetaOmegaKappa.R")

##
## *****
## Kruschke, J. K. (2015). Doing Bayesian Data Analysis, Second Edition:
## A Tutorial with R, JAGS, and Stan. Academic Press / Elsevier.
## *****

fileNameRoot = "Exercise4-"
graphFileType = "png"
# Generate the MCMC chain:
mcmcCoda = genMCMC( data=myData , sName="s" , yName="y" ,
numSavedSteps=10000 , saveName=fileNameRoot , thinSteps=10 )

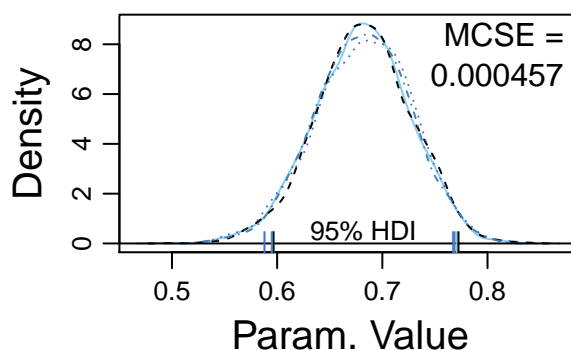
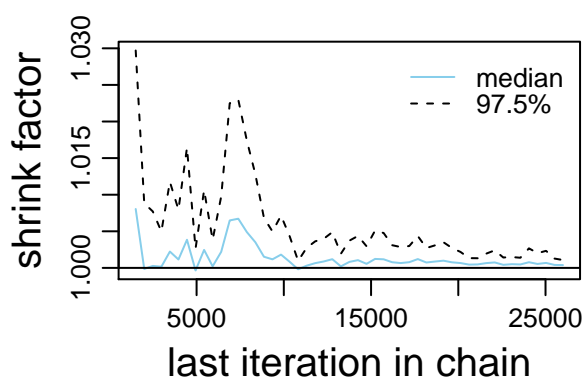
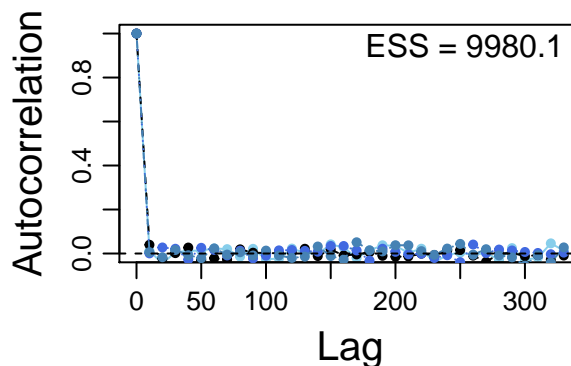
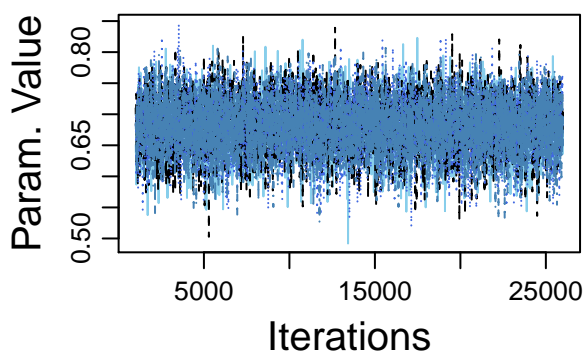
## Compiling model graph
##   Resolving undeclared variables
##   Allocating nodes
## Graph information:
##   Observed stochastic nodes: 500
##   Unobserved stochastic nodes: 7
##   Total graph size: 1046
##
## Initializing model
##
## Burning in the MCMC chain...
## Sampling final MCMC chain...

# Display diagnostics of chain, for specified parameters:
parameterNames = varnames(mcmcCoda) # get all parameter names for reference
for ( parName in parameterNames[c(1:3,length(parameterNames))] ) {
diagMCMC( codaObject=mcmcCoda , parName=parName ,
saveName=fileNameRoot , saveType=graphFileType )
}

# Get summary statistics of chain:
summaryInfo = smryMCMC( mcmcCoda , compVal=0.5 ,
diffIdVec=c(1,2,3,4,5), compValDiff=0.0,
saveName=fileNameRoot )

```

# theta[5]



##	Mean	Median	Mode	ESS	HDImass
## omega	0.49863090	0.49934503	0.49860267	10000.0	0.95
## kappa	10.57502329	9.09678361	6.41932765	10000.0	0.95
## theta[1]	0.31843846	0.31736134	0.30970425	10000.0	0.95
## theta[2]	0.40897635	0.40849883	0.40978728	10000.0	0.95
## theta[3]	0.49966294	0.49987618	0.50076156	9968.6	0.95
## theta[4]	0.59084310	0.59136335	0.58945713	9293.1	0.95
## theta[5]	0.68160619	0.68245928	0.68244190	9709.7	0.95
## theta[1]-theta[2]	-0.09053789	-0.09033178	-0.08814586	10000.0	0.95
## theta[1]-theta[3]	-0.18122448	-0.18105125	-0.17534931	10000.0	0.95
## theta[1]-theta[4]	-0.27240464	-0.27287014	-0.27264018	10000.0	0.95
## theta[1]-theta[5]	-0.36316772	-0.36399943	-0.36339517	10000.0	0.95
## theta[2]-theta[3]	-0.09068659	-0.09107404	-0.08547912	9989.4	0.95
## theta[2]-theta[4]	-0.18186675	-0.18232850	-0.18468106	10000.0	0.95
## theta[2]-theta[5]	-0.27262984	-0.27269753	-0.26691658	10000.0	0.95
## theta[3]-theta[4]	-0.09118016	-0.09093902	-0.09426929	10000.0	0.95
## theta[3]-theta[5]	-0.18194325	-0.18236992	-0.18350112	10000.0	0.95
## theta[4]-theta[5]	-0.09076309	-0.09060728	-0.08768527	10000.0	0.95
##	HDILow	HDHigh	CompVal	PcntGtCompVal	ROPElow
## omega	0.2322431	0.76606607	0.5	49.70	NA
## kappa	2.0127149	23.13535749	NA	NA	NA
## theta[1]	0.2294930	0.40568617	0.5	0.00	NA
## theta[2]	0.3179471	0.50266225	0.5	3.06	NA
## theta[3]	0.4087967	0.59844113	0.5	49.89	NA
## theta[4]	0.5010180	0.68916026	0.5	96.83	NA
## theta[5]	0.5945671	0.77146228	0.5	99.99	NA



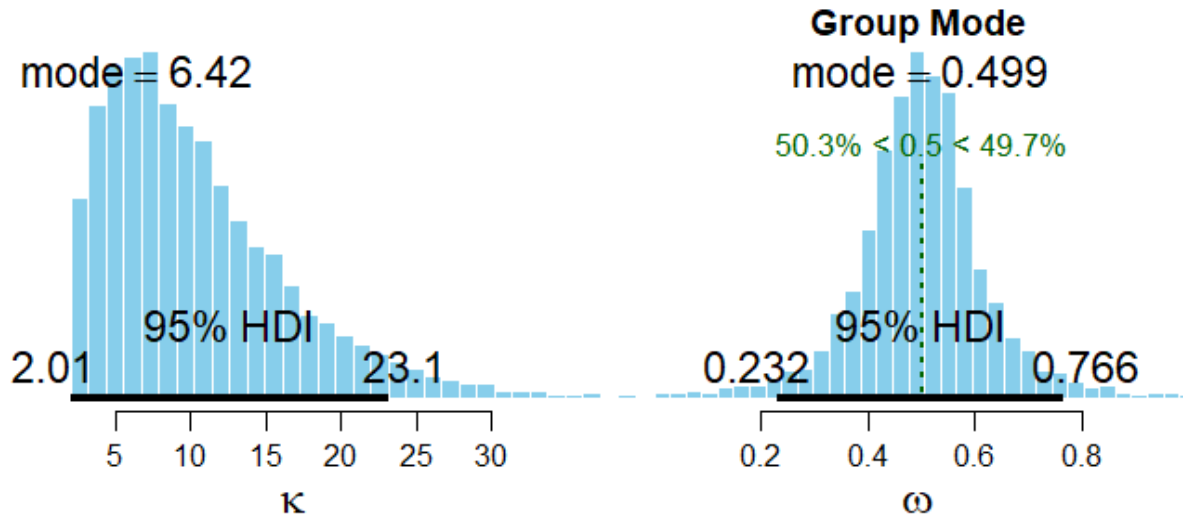


Figure 2:

```
## theta[1]-theta[2] -0.2193714 0.03457214 0.0 8.10 NA
## theta[1]-theta[3] -0.3072866 -0.05521081 0.0 0.34 NA
## theta[1]-theta[4] -0.3978799 -0.13690871 0.0 0.00 NA
## theta[1]-theta[5] -0.4895484 -0.23283192 0.0 0.00 NA
## theta[2]-theta[3] -0.2237148 0.04085347 0.0 8.60 NA
## theta[2]-theta[4] -0.3128959 -0.04911971 0.0 0.36 NA
## theta[2]-theta[5] -0.3975533 -0.13940951 0.0 0.00 NA
## theta[3]-theta[4] -0.2276643 0.03588625 0.0 8.60 NA
## theta[3]-theta[5] -0.3133622 -0.05531593 0.0 0.32 NA
## theta[4]-theta[5] -0.2200607 0.03328258 0.0 8.04 NA
##
## ROPEhigh PcntLtROPE PcntInROPE PcntGtROPE
## omega NA NA NA NA
## kappa NA NA NA NA
## theta[1] NA NA NA NA
## theta[2] NA NA NA NA
## theta[3] NA NA NA NA
## theta[4] NA NA NA NA
## theta[5] NA NA NA NA
## theta[1]-theta[2] NA NA NA NA
## theta[1]-theta[3] NA NA NA NA
## theta[1]-theta[4] NA NA NA NA
## theta[1]-theta[5] NA NA NA NA
## theta[2]-theta[3] NA NA NA NA
## theta[2]-theta[4] NA NA NA NA
## theta[2]-theta[5] NA NA NA NA
## theta[3]-theta[4] NA NA NA NA
## theta[3]-theta[5] NA NA NA NA
## theta[4]-theta[5] NA NA NA NA
```

```
# Display posterior information:
plotMCMC( mcmcCoda , data=myData , sName="s" , yName="y" ,
compVal=0.5 , #rope=c(0.45,0.55) ,
diffIdVec=c(1,2,3,4,5), compValDiff=0.0, #ropeDiff = c(-0.05,0.05) ,
saveName=fileNameRoot , saveType=graphFileType )
```

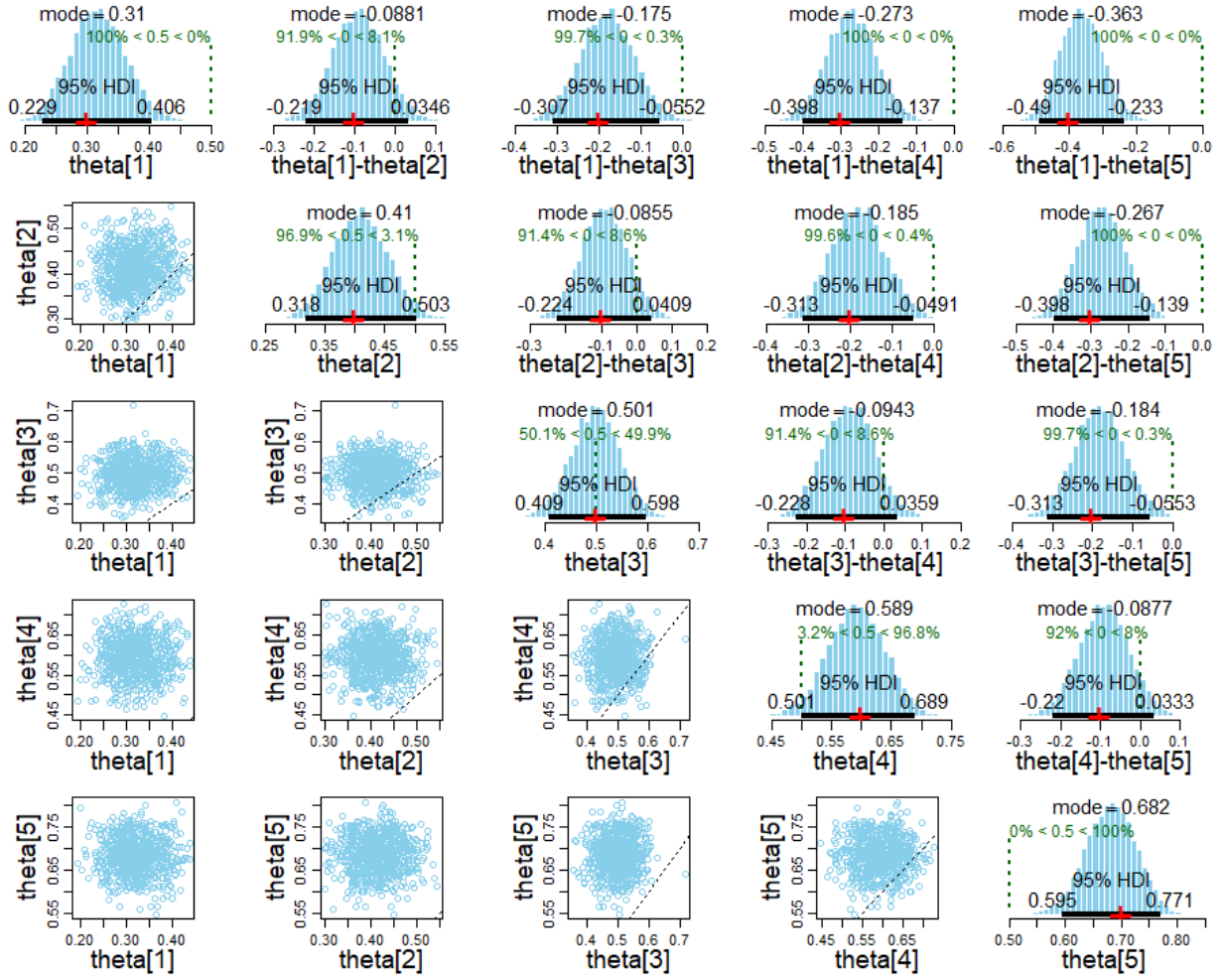


Figure 3:

The posterior showed very small shrinkage when prior on kappa was set with mean=1 as the prior emphasizes small kappa values. But, There is significant shrinkage, when prior uniform was used. Bayesian posterior distribution provides more comprehensive and explicit description of the uncertainty of the estimate for all the parameters compared to MLE.

## 5A.

```
z=3
N=9
omega1 = 0.25
omega2 = 1 - omega1
kappa = 12
p1 = 0.5
p2 = 1 - p1
a1 = omega1*(kappa - 2) + 1
b1 = (1 - omega1) * (kappa - 2) + 1
pD = function(z,N,a,b) { exp( lbeta(z+a,N-z+b) - lbeta(a,b) ) }
a2 = omega2*(kappa - 2) + 1
b2 = (1 - omega2) * (kappa - 2) + 1
Bayes_factor = (pD(z,N, a1, b1) * p1)/(pD(z,N, a2, b2) * p2)
post_tails = Bayes_factor/ (1 + Bayes_factor)
post_heads = 1 - post_tails
```

```
show(Bayes_factor)
```

```
## [1] 4.683258
```

```
show(post_tails)
```

```
## [1] 0.8240446
```

```
show(post_heads)
```

```
## [1] 0.1759554
```

The posterior is exactly the opposite to the example given in the book. The posterior odds are 0.213 against the head-biased factory, which is to say 4.68 (i.e.,  $1/0.213$ ) in favor of the tail-biased factory

## 5B.

```
z=6
N=9
omega1 = 0.25
omega2 = 1 - omega1
kappa = 120
p1 = 0.5
p2 = 1 - p1
a1 = omega1*(kappa - 2) + 1
b1 = (1 - omega1) * (kappa - 2) + 1
pD = function(z,N,a,b) { exp( lbeta(z+a,N-z+b) - lbeta(a,b) ) }
a2 = omega2*(kappa - 2) + 1
b2 = (1 - omega2) * (kappa - 2) + 1
Bayes_factor = (pD(z,N, a1, b1) * p1)/(pD(z,N, a2, b2) * p2)
```

```
post_tails = Bayes_factor / (1 + Bayes_factor)
post_heads = 1 - post_tails
```

```
show(Bayes_factor)
```

```
## [1] 0.05020039
```

```
show(post_tails)
```

```
## [1] 0.04780077
```

```
show(post_heads)
```

```
## [1] 0.9521992
```

The posterior is 0.05 in favor of the tail-biased factory.

## 5C.

```
z=6
N=9
omega1 = 0.025
omega2 = 1 - omega1
kappa = 120
p1 = 0.5
p2 = 1 - p1
a1 = omega1*(kappa - 2) + 1
b1 = (1 - omega1) * (kappa - 2) + 1
pD = function(z,N,a,b) { exp( lbeta(z+a,N-z+b) - lbeta(a,b) ) }
a2 = omega2*(kappa - 2) + 1
b2 = (1 - omega2) * (kappa - 2) + 1
Bayes_factor = (pD(z,N, a1, b1) * p1) / (pD(z,N, a2, b2) * p2)
post_tails = Bayes_factor / (1 + Bayes_factor)
post_heads = 1 - post_tails
```

```
show(Bayes_factor)
```

```
## [1] 0.0002858371
```

```
show(post_tails)
```

```
## [1] 0.0002857554
```

```
show(post_heads)
```

```
## [1] 0.9997142
```

The posterior is 0.0002 in favor of the tail-biased factory ie Factory is head biased.

## 5D.

```
z=6
N=9
omega1 = 0.025
omega2 = 1 - omega1
```

```

kappa = 120
p1 = 0.05
p2 = 1 - p1
a1 = omega1*(kappa - 2) + 1
b1 = (1 - omega1) * (kappa - 2) + 1
pD = function(z,N,a,b) { exp( lbeta(z+a,N-z+b) - lbeta(a,b) ) }
a2 = omega2*(kappa - 2) + 1
b2 = (1 - omega2) * (kappa - 2) + 1
Bayes_factor = (pD(z,N, a1, b1) * p1)/(pD(z,N, a2, b2) * p2)
post_tails = Bayes_factor / (1 + Bayes_factor)
post_heads = 1 - post_tails

show(Bayes_factor)

## [1] 1.504406e-05

show(post_tails)

## [1] 1.504383e-05

show(post_heads)

## [1] 0.999985

```

The posterior is negligibly in favor of the tail-biased factory ie Factory is highly head biased.