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#####1a#####
options(scipen=999) #for removing scientific notation on the plots

n = 50
s = 13
#alpha and beta in prior Beta distribution
alpha0 = 5
beta0 = 5
#alpha and beta in posterior Beta distribution
alpha = alpha0 + s
beta = beta0 + (n - s)

#true mean and standard deviation of the posterior Beta distribution
(formulas from wikipedia for Beta distribution)
true_mean = alpha / (alpha + beta)
true_sd = sqrt(alpha * beta / ((alpha + beta)^2 * (alpha+beta+1)))

draws = seq(5000, 500000, 5000) #different number of draws, i.e. sample
sizes to use
means = c(1:length(draws)) #vector to store the means of the different
sample sizes
sds = c(1:length(draws)) #vector to store the sd's of the different sample
sizes

#for each of the different number of draws, compute and store the estimated
mean and sd.
#storing the absolute value for easier comparison.
for (i in 1:length(draws)) {
  set.seed(12345)
  data = rbeta(draws[i], alpha, beta)
  mean = mean(data)
  sd = sd(data)
  means[i] = abs(true_mean - mean)
  sds[i] = abs(true_sd - sd)
}

#As we see in the plot, the difference between the true mean/sd and the
estimated mean/sd from the simulations
#go to 0 as we increase the number of draws, i.e. the posterior mean and sd
converges to the true values of 0.3 and 0.05867387.
max_y = max(means, sds)
plot(draws, means, type="l", lwd = 2, col="blue", ylim=c(0,max_y), main =
"Deviance from true mean and sd for different number of draws",
      xlab="Number of draws", ylab="Deviance between true mean/sd and
simulated mean/sd" )
points(draws, sds, type="l", lwd = 2, col="green")
legend(x = max(draws)*0.8, y = max_y*0.95, legend = c("mean", "sd"), col =
c("blue","green"), lwd = 3)

#####1b#####
#pbeta gives the distribution function for the Beta distribution,
#i.e. the accumulated probability mass up to some value (area under curve
less or equal to the value)
true_prob = pbeta(0.3, alpha, beta)
true_prob
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nDraws = 10000
set.seed(12345)
data = rbeta(nDraws, alpha, beta)
#using our 10000 draws from the posterior,
#we can calculate the probability by taking number of samples < 0.3 divided
by total number of samples
sim_prob = length(data[data<0.3]) / nDraws
sim_prob

#The probability from simulation with 10000 draws, 0.5156, is very close to
the exact probability of 0.5150.

#Plot of density estimates of our data, a value of around 0.515 looks
reasonable.
plot(density(data))
abline(v=0.3, col="red")

#####1c#####
nDraws = 10000
set.seed(12345)
data = rbeta(nDraws, alpha, beta)

#posterior distribution
hist(data, breaks=25)
plot(density(data), main = "Density estimation of posterior distribution")

#simulating draws from the posterior distribution of the log-odds
#(logit maps the probability values from (0,1) to (-inf, inf))
log_odds = log(data / (1-data))

#posterior distribution of the log-odds
hist(log_odds, breaks=25)
plot(density(log_odds), main = "Density estimation of posterior
distribution of log_odds")
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#####2a#####
data = c(33, 24, 48, 32, 55, 74, 23, 76, 17)
n <- length(data)

mju = 3.5
tao2 = sum((log(data)-mju)^2)/n

NDraws = 10000
PostDraws = c(1:NDraws)
set.seed(123465)
#drawing 10000 sigma^2 from the inv-chi^2 distribution
PostDraws = ((n)*tao2)/rchisq(NDraws,n)

plot(density(PostDraws), xlim=c(0,2), main = expression(paste('Posterior
distribution of ',sigma^2,)))

#####2b#####
#phi(z) is the cumulative distribution function (CDF) for the standard
normal distribution with mean 0 and variance 1.
#pnorm gives the distribution function for the Normal distribution with
default mean=1 and sd=1 (the CDF),
#i.e. the accumulated probability mass up to some value (area under curve
less or equal to the value)
G = 2*pnorm(sqrt(PostDraws/2)) - 1
plot(density(G), main = "Posterior distribution of the Gini coefficient G
for the current data set ")

#####2c#####
#estimation of the the 95% equal tail credible interval using mean and sd
mean = mean(G)
sd = sd(G)
lowerBound = mean - 1.96*sd
upperBound = mean + 1.96*sd
lowerBound
upperBound

#more exact values using qnorm
lowerBound = qnorm(0.025, mean, sd)
upperBound = qnorm(0.975, mean, sd)
lowerBound
upperBound

plot(density(G), main = "Posterior distribution of the Gini coefficient G
for the current data set, \n with 95% equal tail credible interval. ")
abline(v=lowerBound, col="red")
abline(v=upperBound, col="red")

#####2d#####
#extract x- and y-values from the density estimate and sort these on y-
value
#density = density(G, n=10000)
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```
density = density(G)
x = density$x
y = density$y
xy = cbind(x,y)
xy_sorted = xy[order(xy[,2],decreasing=TRUE),]

#calculate what value 95% of the accumulated y-values corresponds to, i.e.
the accumulated value to stop at
#when deciding which (x,y)-pairs to look at
stop_value = sum(xy_sorted[,2])*0.95

#accumulated sum of the sorted y-values
#find out at which index we reach 95% mass (i.e. the stop_value),
#then index 1 to stop_index corresponds to 95% mass
acumulatedMass <- function(stop_val) {
  for (i in 1:length(xy_sorted)) {
    if (sum(xy_sorted[1:i,2]) > stop_val) {
      return (i-1)
    }
  }
}
stop_index = acumulatedMass(stop_value)

#alternative to using above function:
#cumSum = cumsum(xy_sorted[,2])
#stop_index = min(which(cumSum > stop_value)) - 1

#only keep the 95% of the mass corresponding to highest densities
xy_sorted_95 = xy_sorted[1:stop_index,]

#find the indexes corresponding to lower and upper bound
lower_index = which.min(xy_sorted_95[,1])
upper_index = which.max(xy_sorted_95[,1])
lower_index
upper_index

#extract actual lower and upper bounds
HPDIlower = xy_sorted_95[lower_index,1]
HPDIupper = xy_sorted_95[upper_index,1]
HPDIlower
HPDIupper

plot(density(G), main = "Posterior distribution of the Gini coefficient G
for the current data set, \n with 95% Equal Tail Credible Interval, \n and
95% Highest Posterior Density Interval HPDI ")
legend(x = 0.6, y = 5, legend = c("Equal Tail Credible Interval", "HPDI"),
col = c("red","blue"), lwd = 3)
abline(v=lowerBound, col="red")
abline(v=upperBound, col="red")
abline(v=HPDIlower, col="blue")
abline(v=HPDIupper, col="blue")
```

```
#####3a#####
degrees = c(285, 296, 314, 20, 299, 296, 40, 303, 326, 308)
radians = c(1.83, 2.02, 2.33, -2.79, 2.07, 2.02, -2.44, 2.14, 2.54, 2.23)

mju = 2.51
lambda = 1
besselDegree = 0

#posterior proportional to likelihood * prior
#likelihood proportional to exp(k*cos(y-mju)) / I0(k)
#K~Exp(lambda=1) which gives the prior: lambda*exp(-lambda*k)
posterior = function(k, y, mju, degree, lambda) {
  #posterior proportional to:
  posterior = prod( exp(k*cos(y-mju))/besselI(k, degree) ) * lambda*exp(-
lambda*k)
  #posterior = prod( exp(k*cos(y-mju))/besselI(k, degree) ) * dexp(k,
rate=lambda)
}

#grid of k-values to plot over
gridstep = 0.005
k = seq(0, 7, gridstep)

#calculate and store the value for each of the k-values
post = c(1:length(k))
for(i in 1:length(k)) {
  post[i] = posterior(k[i], radians, mju, besselDegree, lambda)
}

#normalizing the posterior distribution of k so that it integrates to 1
post = post/(sum(post)*gridstep)
plot(k, post, type="l", main="Posterior distribution of k", col="blue")


#####3b#####
#the approximate posterior mode of k is the largest value in the posterior
approx_post_K = k[which.max(post)]
approx_post_K
plot(k, post, type="l", main="Posterior distribution of k", col="blue")
abline(v=approx_post_K, col="red")
```