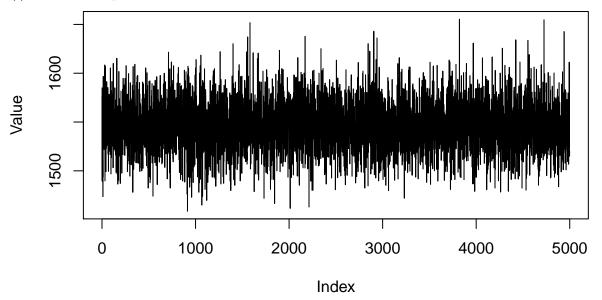
TDDE07 - Lab 3

Sebastian Callh, Jacob Lundberg 4 maj 2018

1. Normal model, mixture of normal model with semi-conjugate prior

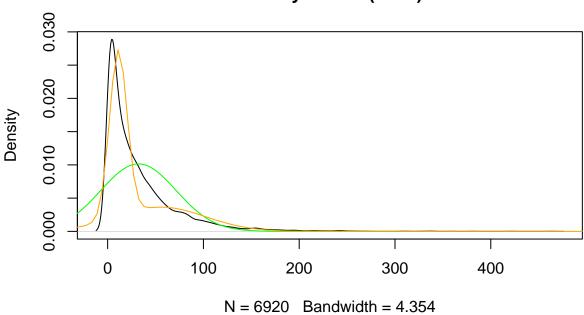
- a) Normal model
- (i) Gibbs sampler



(ii) - Analysis

- b) Mixture normal model
- c) Graphical comparison

density.default(x = x)



- 2. Time-series models in Stan
- $\mathbf{a})$
- b)
- $\mathbf{c})$

d)

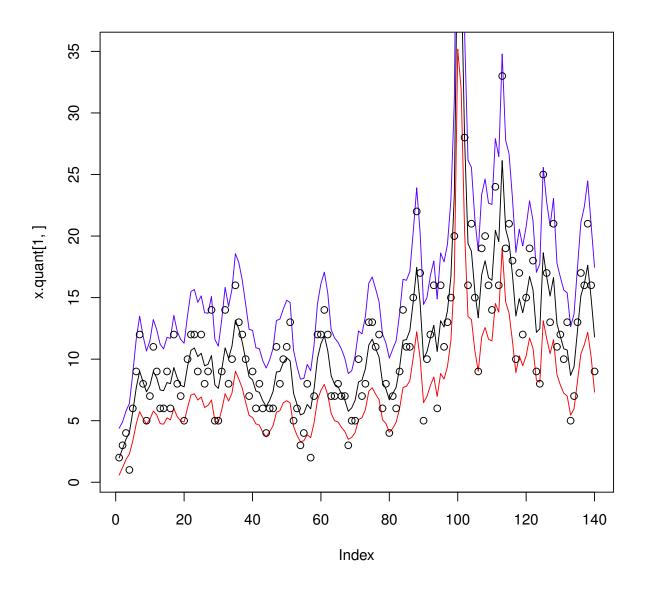


Figure 1: "Posterior without sigma prior"

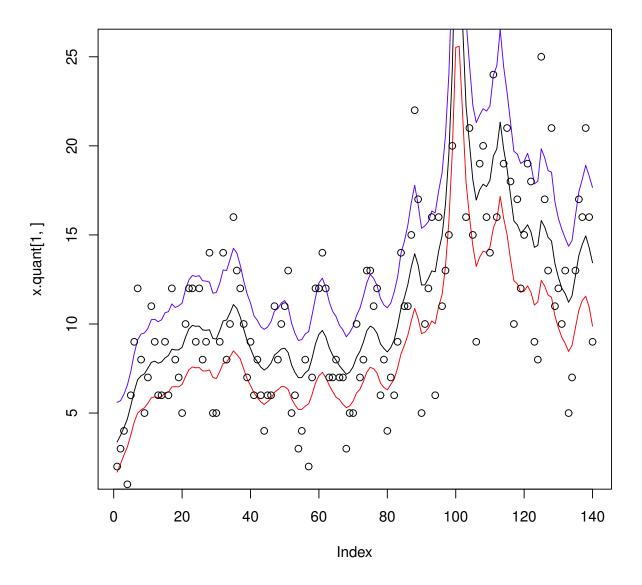


Figure 2: "Posterior with sigma $0.02~\mathrm{prior}$ "

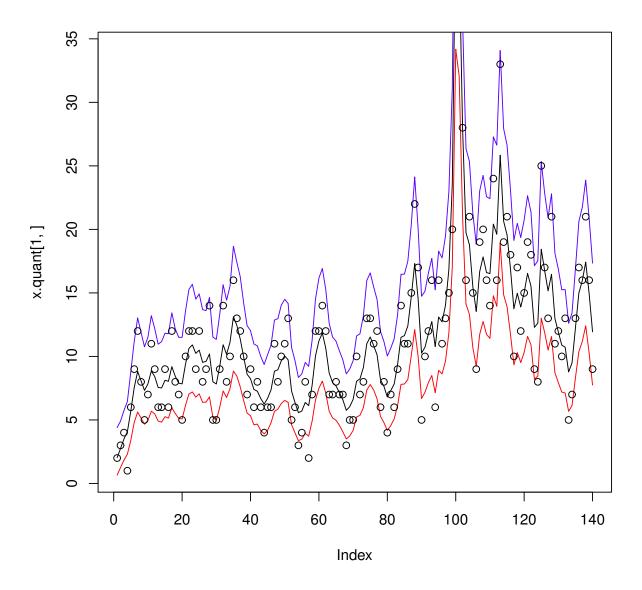


Figure 3: "Posterior with sigma prior"

Appendix

```
# 1 Normal model, mixture of normal model with semi-conjugate prior
# a) Normal model
data <- read.table("rainfall.dat", header=FALSE)</pre>
       <- 20 # 0.5 cm
muO
tau0 <- 5 # Variance of expected rainfall
nu0
       <- 3 # Variance of expected value of variance
sigma0 <- 5 # Expected value of variance
nIter <- 5000
theta0 <- c(20, 2)
       <- data[,1]
х
       <- length(x)
rinvchisq <- function(vx, sigmax, draws) {</pre>
  vx*sigmax/rchisq(draws, vx)
}
Mu.Conditional.Posterior.Draw <- function(sigma2) {</pre>
  taun <- sqrt(1/(n/sigma2 + 1/tau0^2))
      <- (n/sigma2) / (n/sigma2 + 1/tau0^2)
 mun \leftarrow w*mean(x) + (1 - w) * mu0
  rnorm(1, mun, taun)
}
Sigma.Conditional.Posterior.Draw <- function(mu) {</pre>
         <- n + nu0
  sigman \leftarrow (nu0*sigma0^2 + sum((x-mu)^2)) / nun
 rinvchisq(nun, sigman, 1)
}
Gibbs <- function(theta_t) {</pre>
        <- Mu.Conditional.Posterior.Draw(theta_t[2])</pre>
  sigma2 <- Sigma.Conditional.Posterior.Draw(mu)</pre>
  c(mu, sigma2)
           <- matrix(rep(0, nIter*2), nrow = nIter)
thetas[1,] <- theta0
for(i in 2:nIter) {
  thetas[i,] <- Gibbs(thetas[i-1,])</pre>
plot.normal.approximation <- function () {</pre>
  plot(thetas[-1,2],
       type = '1',
       ylab = 'Value')
}
# b) Mixture normal model
```

```
# Model options
nComp <- 2
                             # Number of mixture components
# Prior options
alpha <- 10*rep(1,nComp) # Dirichlet(alpha)
muPrior <- rep(mu0,nComp)
                               # Prior mean of mu
tau2Prior <- rep(tau0,nComp) # Prior std of mu</pre>
sigma2_0 <- rep(sigma0,nComp) # s20 (best guess of sigma2)</pre>
nu0
          <- rep(nu0,nComp)
                               # degrees of freedom for prior on sigma2
#source("NormalMixtureGibbs.R")
# c) Graphical comparison
            <- mean(thetas[,1])
gibbs.mu
gibbs.sigma <- sqrt(mean(thetas[,2]))</pre>
delta <- 0.05
grid <- seq(-100, 300, delta)
plot.graphical.comparison <- function () {</pre>
  plot(density(x), col = 'black')
  lines(grid, dnorm(grid, gibbs.mu, gibbs.sigma), type = 'l', col = 'green')
  lines(xGrid, mixDens, type = 'l', col = "orange")
}
# 2 Time series models in Stan
library(rstan)
options(mc.cores = parallel::detectCores())
rstan_options(auto_write = TRUE)
# a)
ar.process <- function (phi, init, sigma, T) {</pre>
   y <- rep (0, T)
    y[1] <- init
    for (t in 2:T) {
        y[t] \leftarrow mu + phi*(y[t-1] - mu) + rnorm(1, 0, sigma)
    }
    У
}
      <- 200
Т
      <- 10
mu
phi1 <- 0.3
phi2 <- 0.95
s <- sqrt(2)
x <- ar.process(phi1, mu, s, T)
y <- ar.process(phi2, mu, s, T)
plot(x, type ='l')
# b)
```

```
x.fit <- stan(file = "time-series.stan",</pre>
             data = list(
                 x = x
                 N = T
             ))
y.fit <- stan(file = "time-series.stan",</pre>
             data = list(
                 x = y
                 N = T
             ))
posterior.mean.x <- get_posterior_mean(x.fit)</pre>
posterior.mean.y <- get_posterior_mean(y.fit)</pre>
head(posterior.mean.y)
head(posterior.mean.x)
             <- posterior.mean.x[1, 5]</pre>
mu.x.post
sigma.x.post <- posterior.mean.x[2, 5]</pre>
phi.x.post <- posterior.mean.x[3, 5]</pre>
x.params <- extract(x.fit, pars = c("mu", "phi"))</pre>
y.params <- extract(y.fit, pars = c("mu", "phi"))</pre>
plot(x.params$mu, x.params$phi)
plot(y.params$mu, y.params$phi)
              <- posterior.mean.y[1, 5]</pre>
mu.y.post
sigma.y.post <- posterior.mean.y[2, 5]</pre>
phi.y.post <- posterior.mean.y[3, 5]</pre>
z.x <- ar.process(phi.x.post, mu.x.post, sigma.x.post, T)</pre>
z.y <- ar.process(phi.y.post, mu.y.post, sigma.y.post, T)</pre>
plot(y.fit)
summary(y.fit)
plot(x, type = 'l', col = 'red')
lines(z, col = 'blue')
fit
plot(fit)
d < -0.05
grid \leftarrow seq(0, 2, d)
plot(grid, dnorm(grid, 0, 0.02))
# c)
campy.data <- as.vector(read.table("campy.dat", header = TRUE)[,1])</pre>
c.fit <- stan(file ="campy.stan",</pre>
               data = list (
                   c = campy.data,
                   N = length(campy.data)
               ))
params <- extract(c.fit, pars = c("mu", "sigma"))</pre>
x <- extract(c.fit, pars = "x")</pre>
```

```
mean(params$sigma)
theta.t \leftarrow exp(x$x)
x.mean <- apply(theta.t, 2, mean)</pre>
x.quant <- apply(theta.t, 2, quantile, probs=c(0.025,0.975))</pre>
setEPS()
postscript("posterior-with-sigma-0.02-prior.eps")
plot(x.quant[1,], type = 'l', col='red')
lines(x.quant[2,], type = 'l', col='blue')
lines(x.mean, type = '1')
points(campy.data)
dev.off()
c.df <- as.data.frame(fit)</pre>
head(as.matrix(c.fit)[,1])
# d)
\# posterior sigma = 0.2603307 with uniform
# posterior sigma = 0.2481805 with 0.15
\# posterior sigma = 0.1074629 with 0.02
```