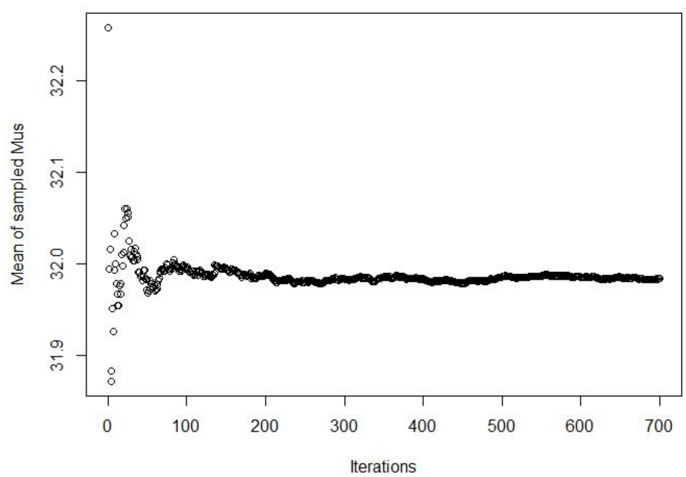
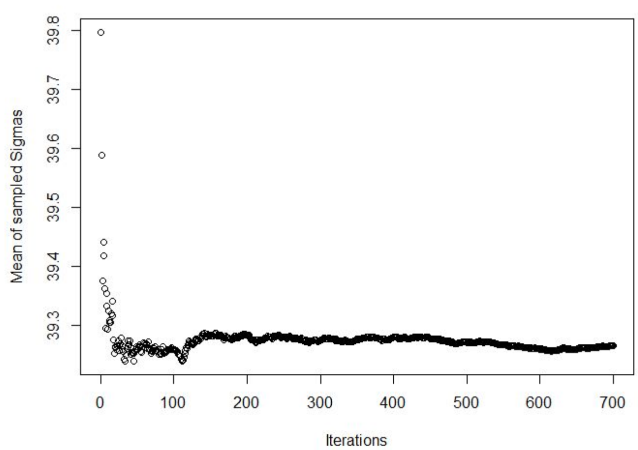
Lab 3

1 a) ii)
We assume a prior for mu with mu0 = 0, sigma0 = 5.
We assume a prior for sigma with sigma0 = 5 and v0 = 20.

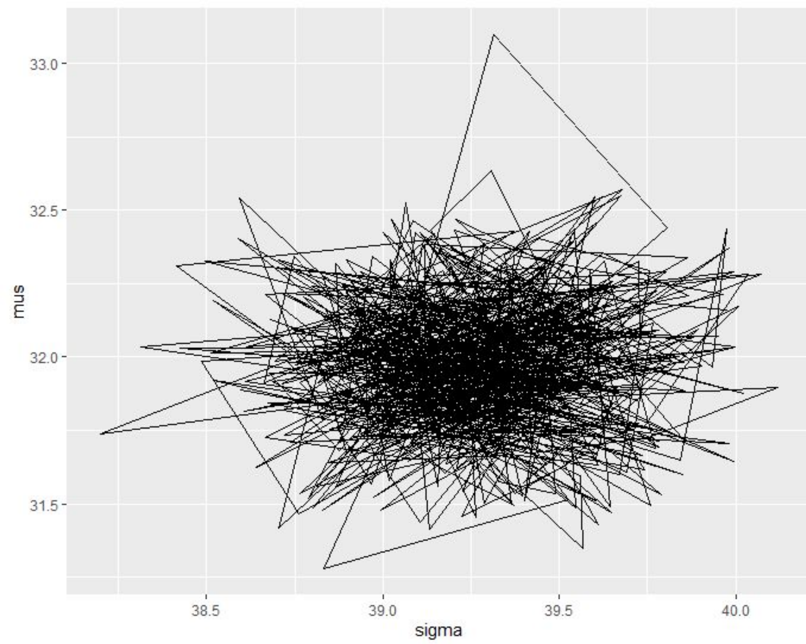
We sample from our distribution of mu and sigma, and use the sampled mu in the distribution for sigma, and then the sampled sigma in the distribution of mu e.t.c.

We save the mean of sigma and mu after each iteration to observe the convergence of the expected value of sigma and mu, plotted below.





The following is the plotted trajectories for mu and sigma, on the x and y axis respectively:



As we can see, the variables do not seem to be correlated as the data plotted has no skewed pattern.

1 b)

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We set the priors we set are the following:

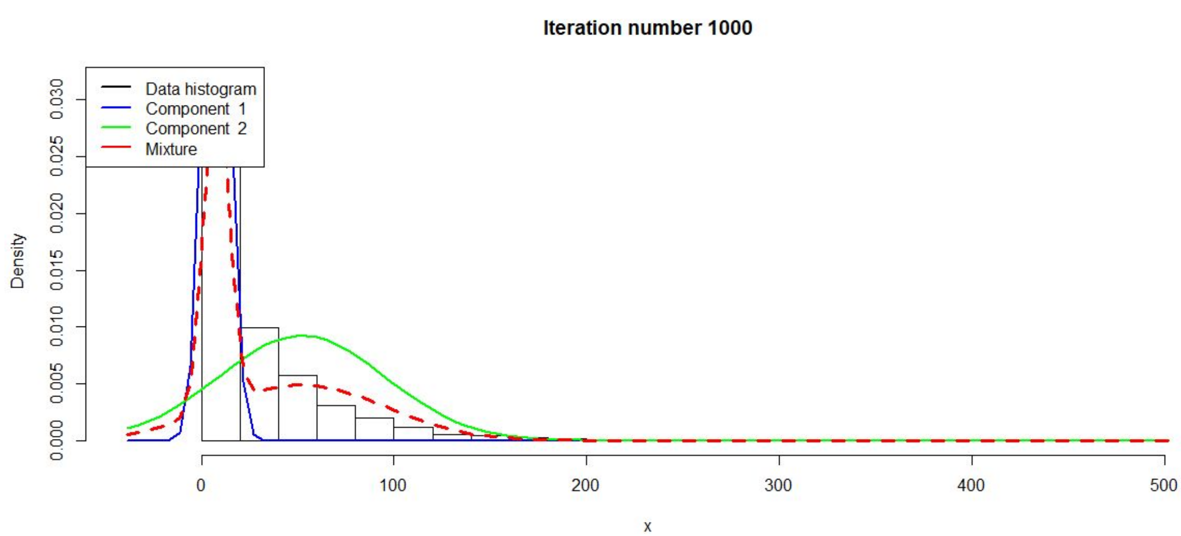
We assume that the mixture model’s two distributions will correspond to the distribution of rainy days and the distribution for non-rainy days. We consider the first distribution N1 as the distrubution for non-rainy days and the second distribution N2 as the distribution for rainy days. Therefor, we set our prior values according to our beliefs of the probability of rain e.t.c.

Alpha to 6,1 as this corresponds to a beta(6,1) distribution. This means that alpha will have a mean of 6/7, which means that 6/7 points are on average considered as not-rain, which is our prior belief. We further expand our beliefs saying that when it rains we think it will rain on average 60/100 inches. We also naturally set the mean of non-rainy days to 0 . This is shown in our values for the muPrior = (0,60). We believe that our uncertainty of how much it rains is bigger than how much rain there is on days considered as ‘non-rain’, which means that we set our tau2prior much larger for N2. We also believe that the standard deviation for rain is larger for N2, which means that we set sigma2 5 times as large for N2 than N1. We also estimate our prior beliefs to be worth 80 samples, which is <10% of the total sample amount of the data. We therefor think that our prior beliefs matter about one tenth relative the data provided.

alpha <- c(6,1) # Dirichlet(alpha)

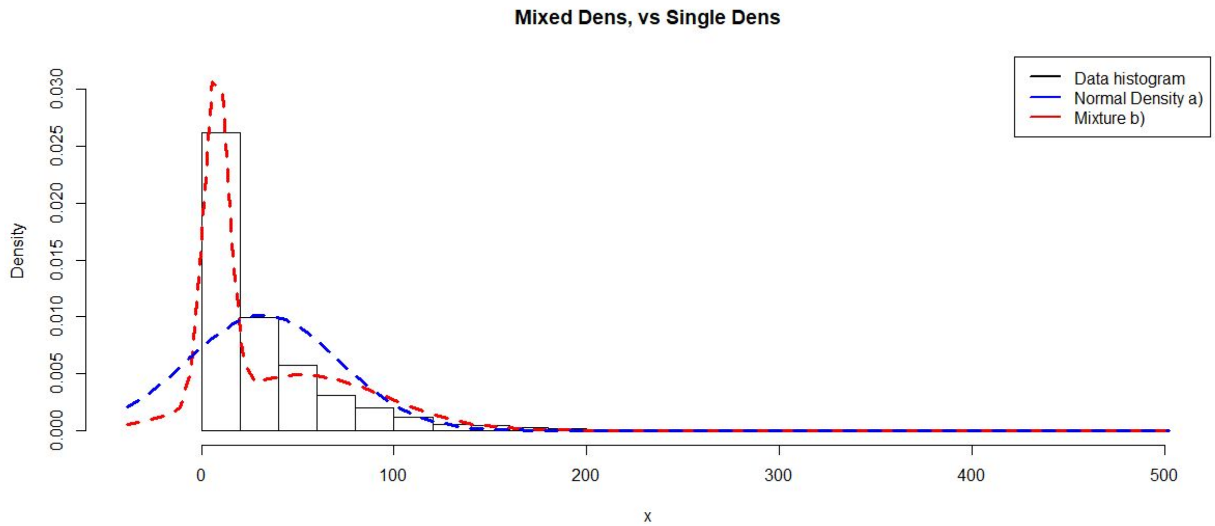
```
muPrior <- c(0,60) # Prior mean of mu

tau2Prior <- c(1, 25) # Prior std of mu
sigma2_0 <- c(1, 5) # s20 (best guess of sigma2)
nu0 <- rep(80,nComp) # degrees of freedom for prior on sigma2
```

With these parameters the Gibbs sampling augmentation algorithm converged as shown in the picture below. We believe the mixture model to be a fairly good representation of reality and hence a good convergence. It is reasonable that the blue model (representing non-rainy days) is close to zero with a small variance and that the green model representing the rainy days is flatter with greater variance. One thing to note is that our mixture model can take negative values for the daily precipitation which is not possible in the real world. However, when drawing from this distribution one can just set a rejection criteria for all values below zero to account for this.



1 c)

The three different plots are combined in one figure and shown below:



2 a)

When running the glm to fit the generalized linear model we get the summary result for the coefficients presented below:

Coefficients:

	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	1.07244	0.03077	34.848	< 2e-16	***
PowerSeller	-0.02054	0.03678	-0.558	0.5765	
VerifyID	-0.39452	0.09243	-4.268	1.97e-05	***
Sealed	0.44384	0.05056	8.778	< 2e-16	***
Minblem	-0.05220	0.06020	-0.867	0.3859	
MajBlem	-0.22087	0.09144	-2.416	0.0157	*
LargNeg	0.07067	0.05633	1.255	0.2096	
LogBook	-0.12068	0.02896	-4.166	3.09e-05	***
MinBidShare	-1.89410	0.07124	-26.588	< 2e-16	***

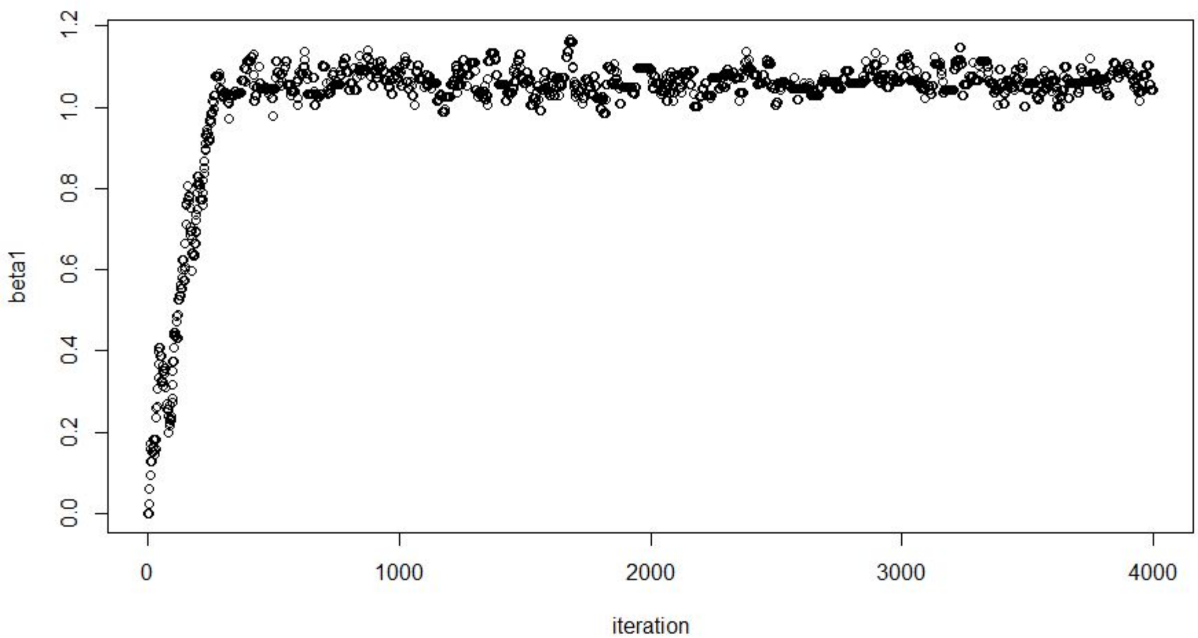
From this we can see that the MinBidShare coefficient is by far the most influential since it has the highest absolute value of 1.89.
The four most significant variables, with their corresponding coefficients are:
MinBidShare: -1.89
Sealed: 0.44
VerifyID: -0.39
majBlem: -0.22

(b)

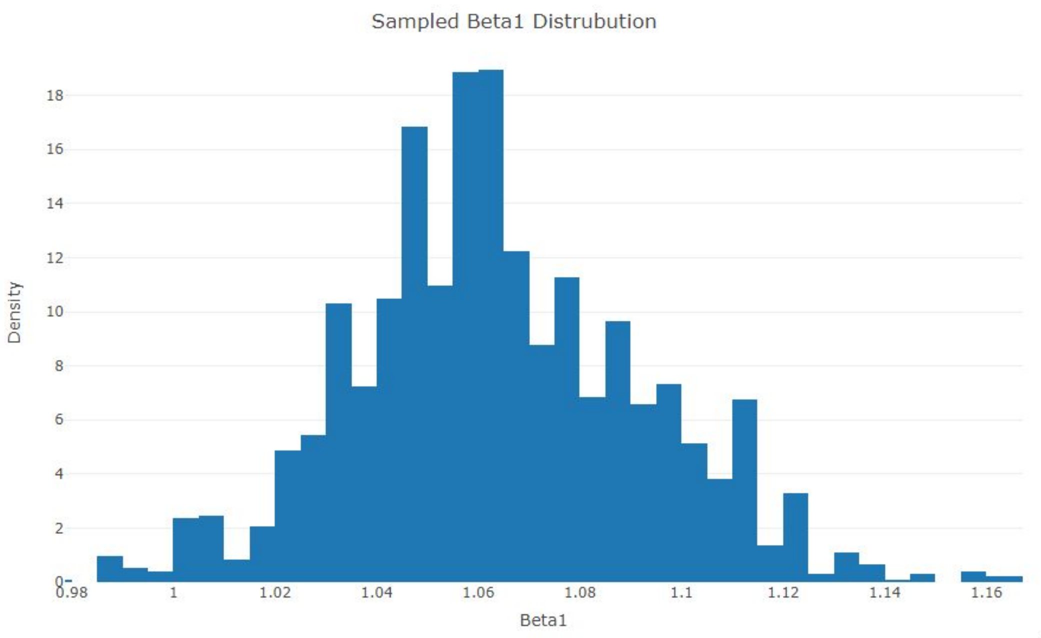
See the code for the log posterior function using the Poisson model and the optim.R approximation.

(c)

The first plot below shows the beta1 for each iteration of our constructed metropolis hasting function and how beta1 clearly convergences to a certain distribution. The converged distribution's mean can be compared to the numeric approximation from optim.R for the first Beta value. Convergence is achieved after about 250 iterations.

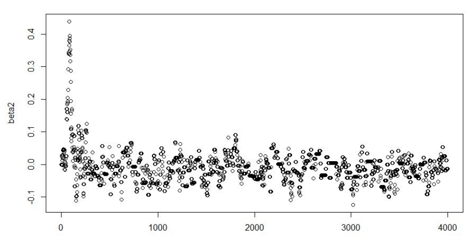


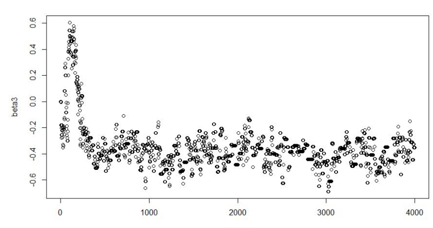
The converged beta1 distribution corresponds to this estimated density plot

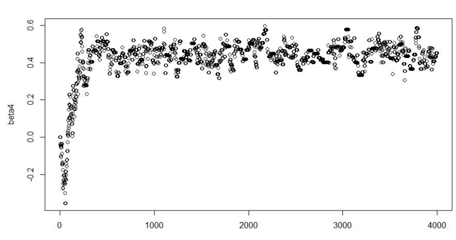


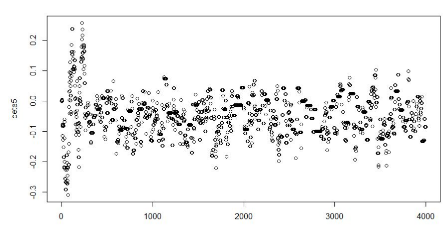
The resulting mean of beta1 was *1.0641* to compare with the *Optim.R* $Beta_1$ = *1.06984118*.

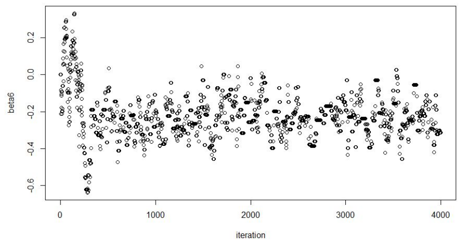
Below are the convergence plots for the remaining betas:

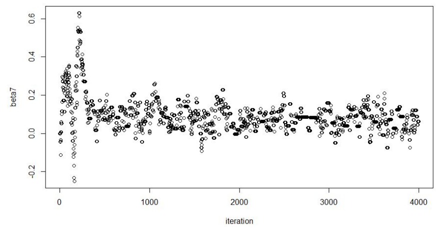


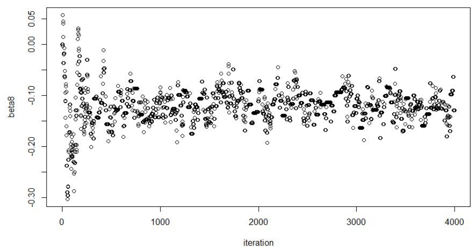


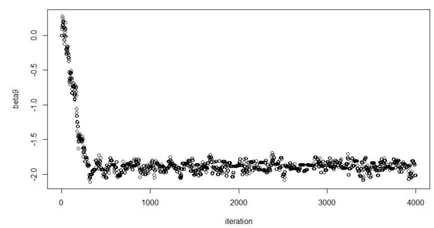












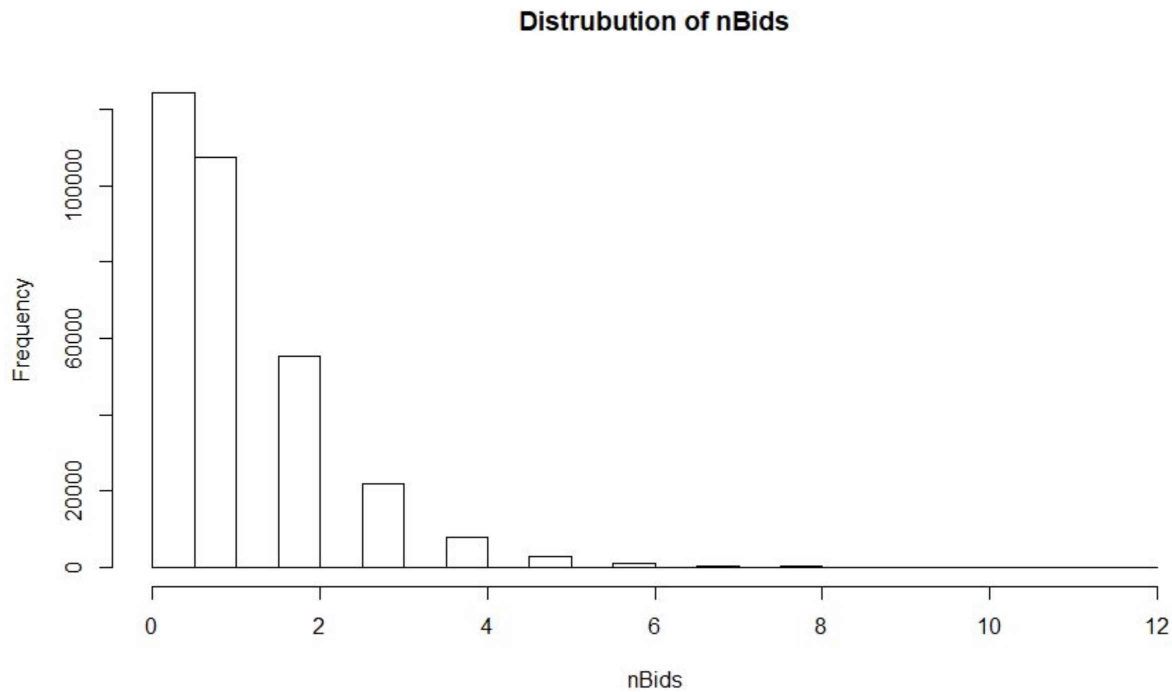
Comparision of beta means

We compare the mean computed numerically from the distribution of betas given from the metropolis hasting's algorithm with the posterior mean from the optim.R.

	B1	*B2*	*B3*	*B4*	*B5*	*B6*	*B7*	*B8*	*B9*
Optim.R	1.07	-0.02	-0.39	0.44	-0.05	-0.22	0.07	-0.12	-1.89
M.H mean	1.06	-0.01	-0.39	0.44	-0.05	-0.24	0.08	-0.12	-1.89
Difference	0.01	0.01	0	0	0	0.02	0.01	0	0

(d)

When plotting the predictive distribution for the characteristics below we simply take a poisson distribution draw iteratively from each beta vector (after a burn-in period of 300 iterations) multiplied with the given feature vector. All draws then becomes our predictive distribution. After that we compute how many of these draws == 0 and divide by the total number of draws. That becomes our prediction on how many auctions that will have zero bids. See summary of this below.



p(no bidders) = 0.387