

# Report

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## 1 INTEGRATING MODELS FOR FACIES PREDICTION

### 1.1 PART A

The course codes were trimmed so that they only output scaled kapur data (function `scaleKapur`). Then, the kapur facies are counted using `table` function and probability (proportion) of each facies is computed.

```
#cleaning variables and closing plots
rm(list=ls())
if (!is.null(dev.list())) dev.off()

#loading packages
require(boot)
require(nnet)
require(RColorBrewer)
require(ggplot2)
require(lattice)
line.colors <- brewer.pal(N.facies, "Dark2")

#Counting facies using 'table' function
facies      = kapur["facies"]
tab.facies  = table(facies)
N.facies    = length(tab.facies)
```

```
tot.obs    = sum(tab.facies)
p.facies   = tab.facies/tot.obs
```

For fitting a beta distribution to the facies, the total counts are used for estimating alpha and beta. dbeta function is then used for calculating the probability of facies proportions. The results are then tabulated to be used by *lattice* package.

```
for (i in 1:N.facies){
  #evaluating the parameters of beta function and facies pdf
  x      = seq(0,1,0.001)
  alpha  = tab.facies+1
  beta   = tot.obs-tab.facies+1
  p.df   = dbeta(x,alpha[i],beta[i])

  #tidy up for lattice package
  current.size = length(x)
  sum.size.pri = current.size+sum.size.pri
  all.prior[(sum.size.pri-current.size):(sum.size.pri-1),1] = x
  all.prior[(sum.size.pri-current.size):(sum.size.pri-1),2] =
    p.df/sum(p.df)
  all.prior[(sum.size.pri-current.size):(sum.size.pri-1),3] =
    rep(paste("facies ",i),length(x))
}
#plotting priors using lattice package
line.colors = brewer.pal(N.facies,"Dark2")
myStrip      = function(which.panel, factor.levels, ...) {
  panel.rect(0, 0, 1, 1,col = line.colors[which.panel],border = 1)
  panel.text(x = 0.5, y = 0.5,font = 2,lab = factor.levels[which.panel])
}
print(xyplot(Probability ~ Proportion|Facies.type,
             data = all.prior[1:sum.size.pri-1,],
             type = "l",lwd = 3,strip = myStrip))
```

## 1.2 PART B

Function prob.facies was prepared for bootstrapping using boot function. This function fits the multinomial regression to the facies and outputs the probability of probability of each facies.

```
#Defining the probability function to be bootstrapped
prob.facies <- function(formula, data, indices){
  selected.data = data[indices,]
```

```

kapur.glm      = multinom(formula,data=selected.data)
pred.glm      = fitted(kapur.glm)
pred.glm      = sortPredByLevels(pred.glm)
most.likely.glm = apply(pred.glm,1,which.max)
tab.pred.facies = table(most.likely.glm)
tot.obs       = sum(tab.pred.facies)
all.fac.name  = names(table(data$facies))
N.facies      = length(all.fac.name)
idxToFac      = all.fac.name
names(idxToFac) = as.character(1:N.facies)
sel.fac.name   = names(tab.pred.facies)
names(tab.pred.facies) = idxToFac[sel.fac.name]
no.occure.facies = setdiff(all.fac.name,sel.fac.name)
prob          = rep(NA,N.facies)
names(prob)    = all.fac.name
if (any(as.integer(no.occure.facies))) {
  prob[no.occure.facies] = 0
}
prob[sel.fac.name] = as.vector(tab.pred.facies)/tot.obs
return(prob)
}

```

Note that when we are using bootstrapping for categorical data, we face two important challenges. First, some facies type may not be sampled and second some facies type may not be predicted. For both of these situations we should put the probability of such facies to zero. Here, facies 2 and 7 occur relatively few times and sometimes they may not be sampled or predicted. Below lines (which are in prob.facies function) are added for detecting unsampled facies and enforcing their probabilities as zero when bootstrapping. Below chunk demonstrates the idea of naming existing facies according to the indeices that come out of which.max function.

```

all.fac.name  = names(table(data$facies))
N.facies      = length(all.fac.name)
idxToFac      = all.fac.name
names(idxToFac) = as.character(1:N.facies)
sel.fac.name   = names(tab.pred.facies)
names(tab.pred.facies) = idxToFac[sel.fac.name]
no.occure.facies = setdiff(all.fac.name,sel.fac.name)
prob          = rep(NA,N.facies)
names(prob)    = all.fac.name
if (any(as.integer(no.occure.facies))) {
  prob[no.occure.facies] = 0
}

```

And finally function `prob.facies` is prepared to be passed to function `boot` to be bootstrapped 300 times.

```
# Bootstrapping using boot function
form      = facies ~ caliper + ind.deep + gamma + r.deep + density

boot.result = boot(formula=form, statistic=prob.facies,
                    data=scaleKapur(kapur), R=N.Boot)
```

### 1.3 PART C

Posteriors are calculated by multiplying the priors and likelihoods. In below code `y` represents the likelihood and `p.df` represents the prior counts for the facies.

```
# Finding and plotting facies posteriors
posterior = p.df * y/sum(p.df * y)
```

and then we plot the posterior of each facies using *ggplot2* package.

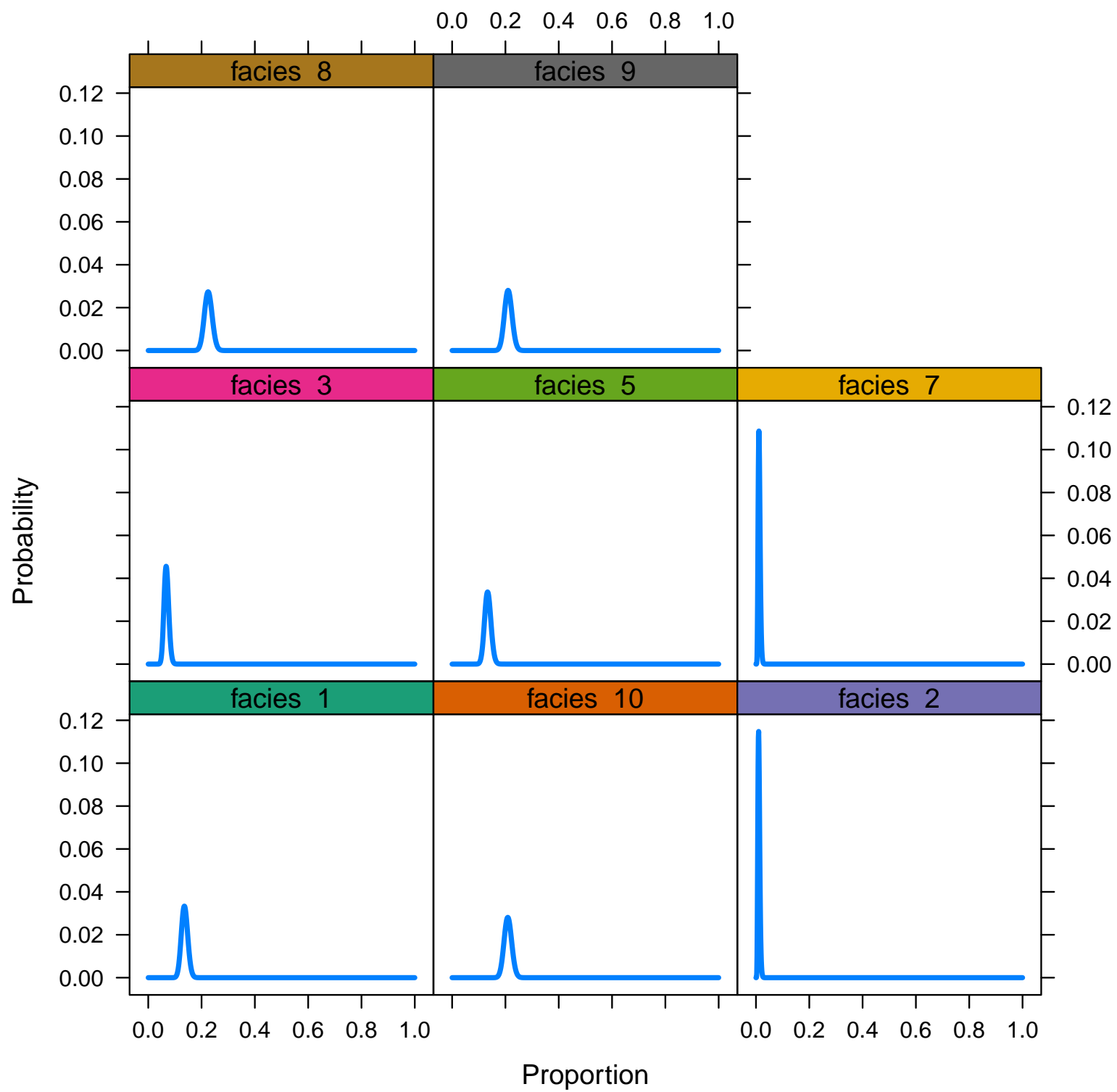
```
df      = data.frame(x,prior,likelihood,posterior)

g[[i]]  = ggplot( df, aes(x)) +
          geom_line(aes(y=prior,colour="prior")) +
          geom_line(aes(y=likelihood,colour="likelihood")) +
          geom_line(aes(y=posterior,colour="posterior"))

g[[i]]  = g[[i]] + xlab(paste("proportion of facies ",
                              names(tab.facies[i]))) + ylab("Probability")+
          scale_colour_manual("",values=c("darkgreen","blue","red"))

require(gridExtra)
for (i in seq(1,8,2)){
  sidebysideplot = grid.arrange(g[[i]], g[[i+1]], nrow=2)
  print(sidebysideplot)
}
```

For facies 1 and 2, the likelihood improves our belief about the proportion of these facies and our model strengthens the priors. The likelihood weakens our confidence (prior) on probabilities of facies 5 and 7. Probabilities of facies 9 and 10 are not affected using bayesian analysis. This may be because their proportions are already high and likelihood also approves the priors to be the best representation of these facies. For facies 3, the likelihood hugely changes our understanding of it's probability. It indicates that most probable proportion of facies 3 is 0.055 and our prior opinion of 0.07 may not be accurate based on new evidence (bootstrapped multinomial model).





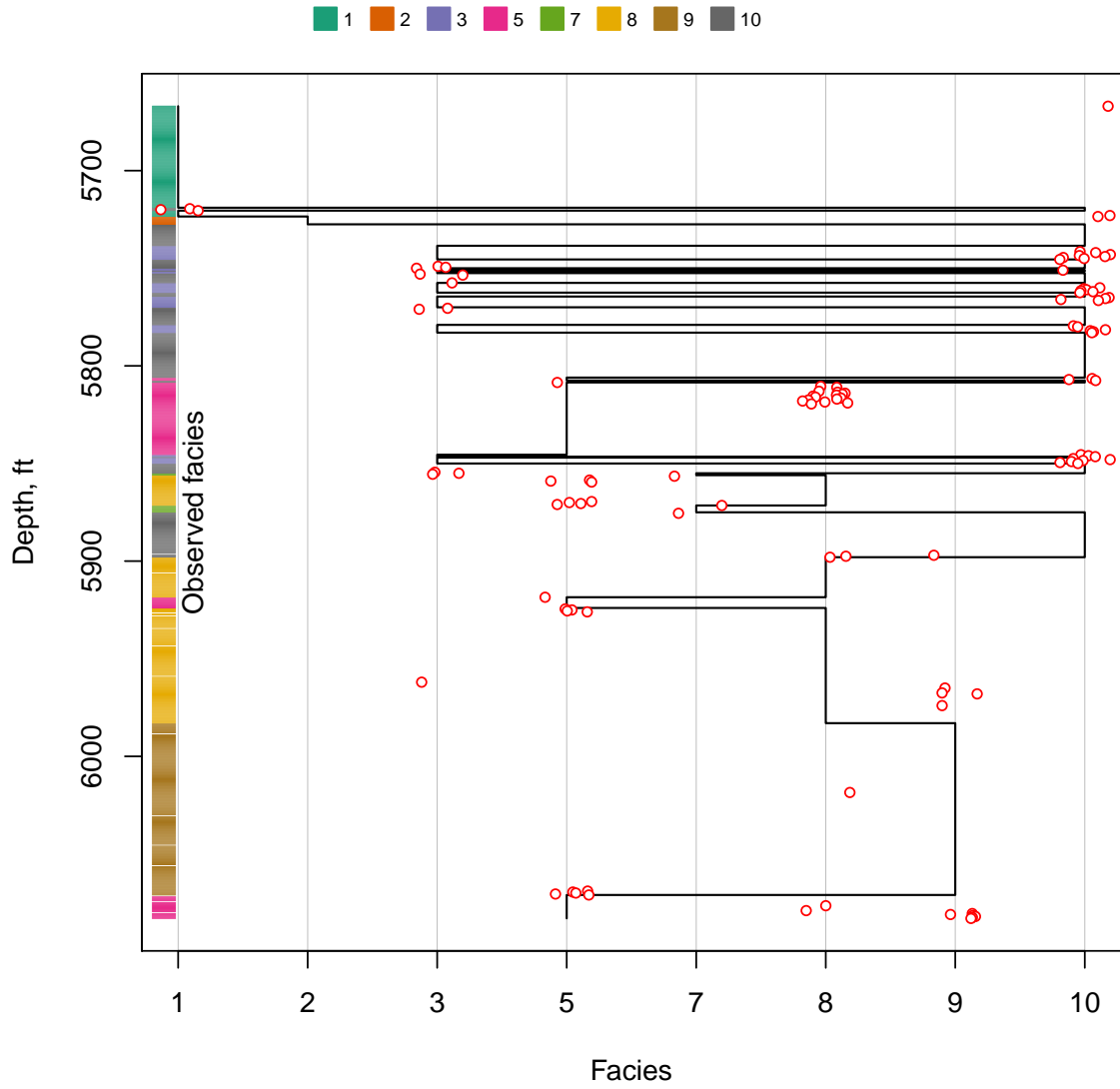
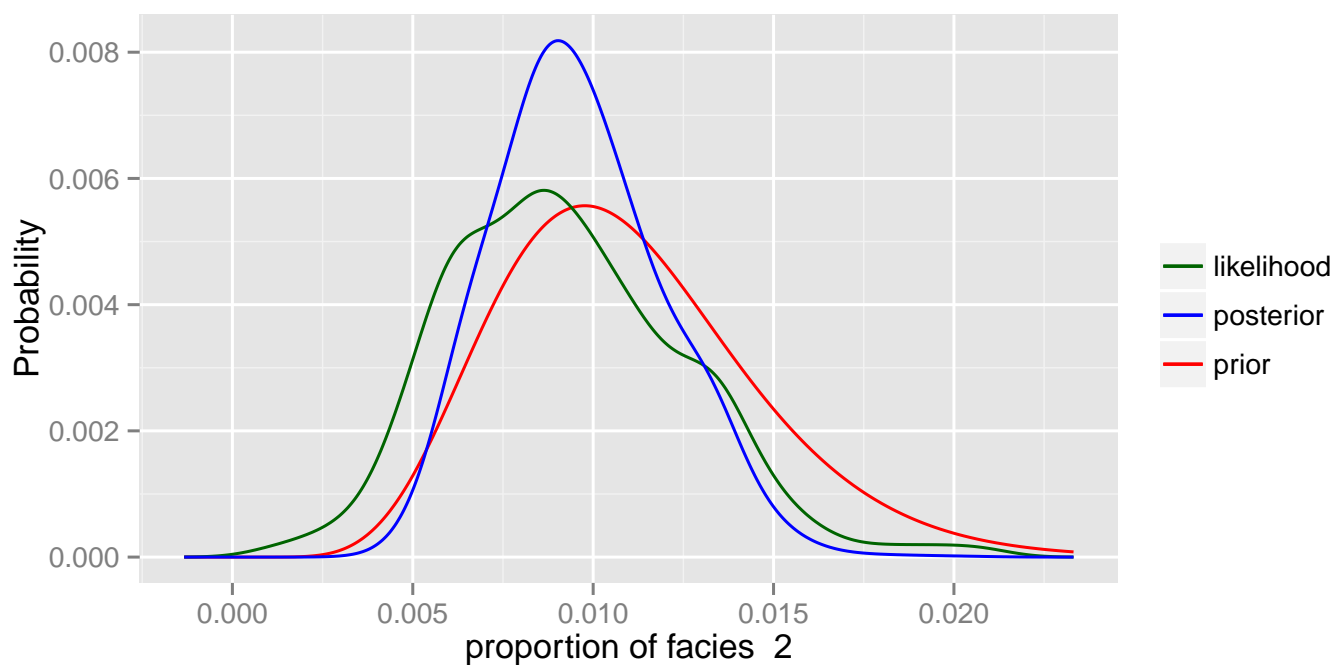
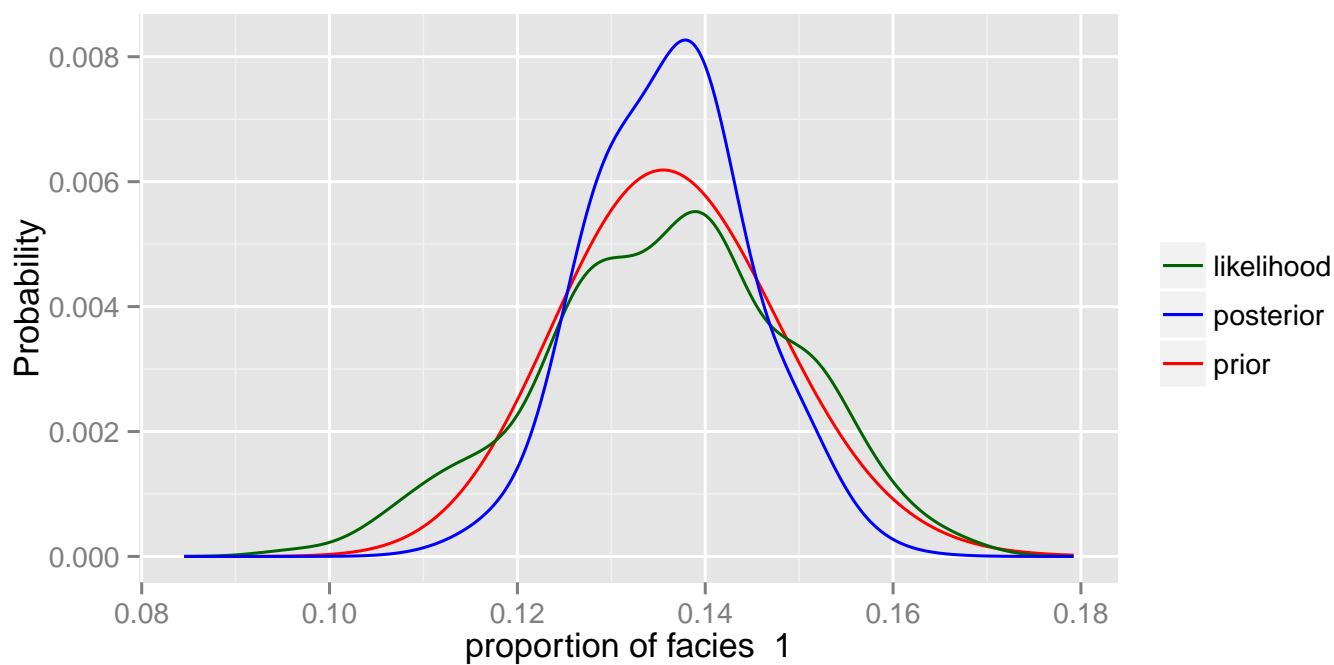
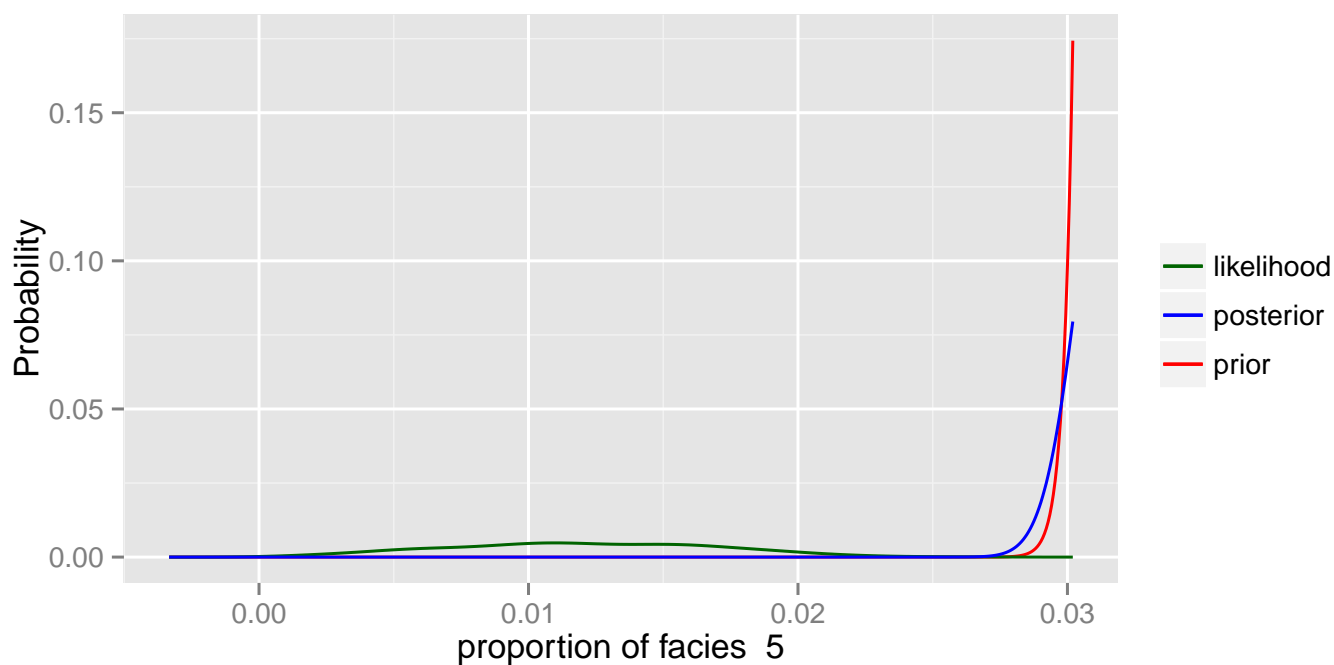
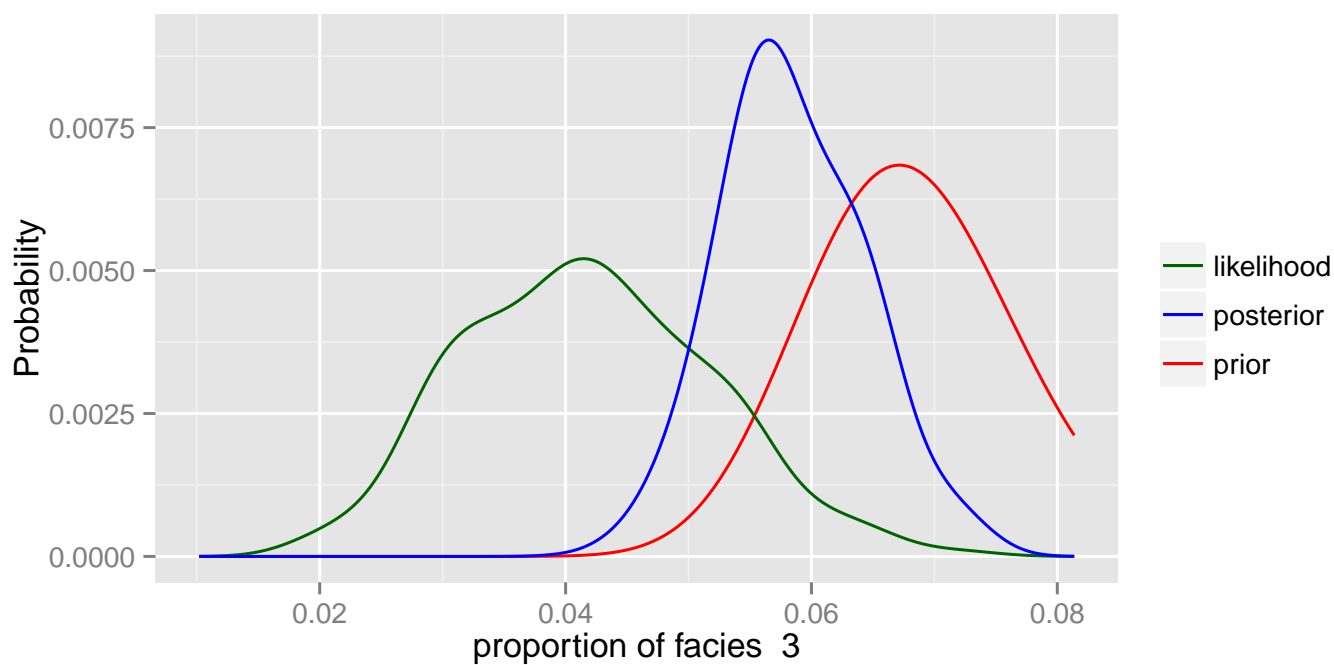
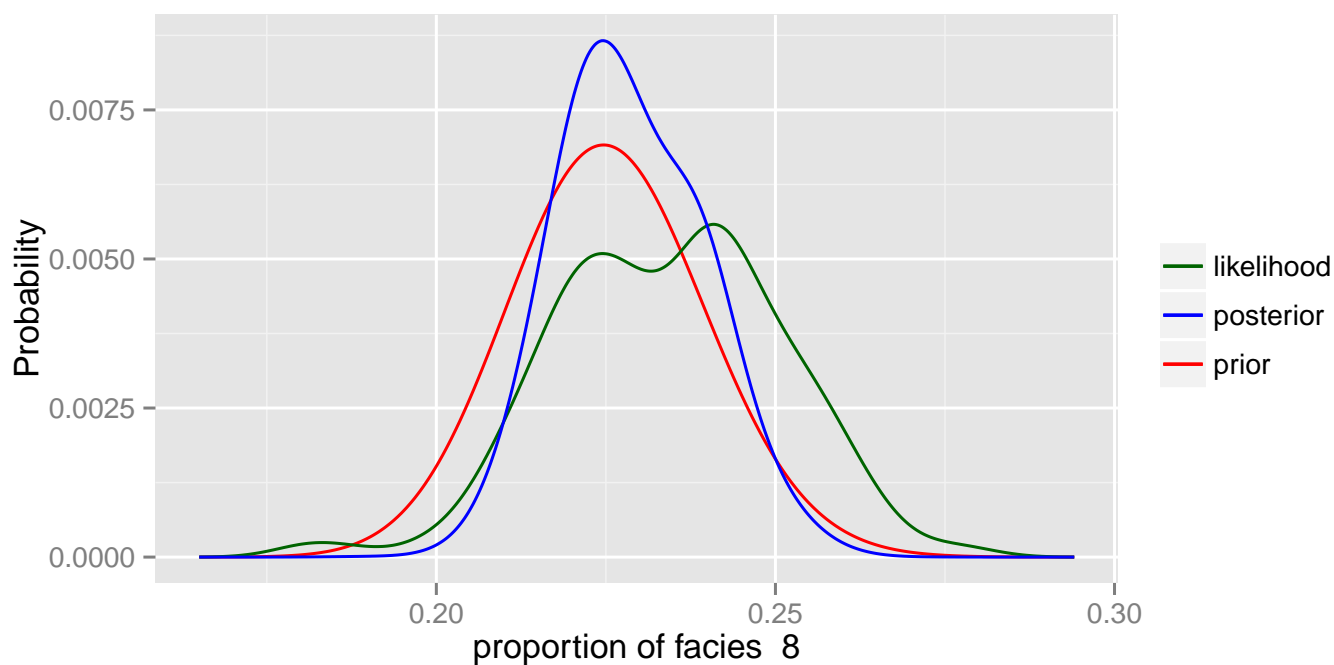
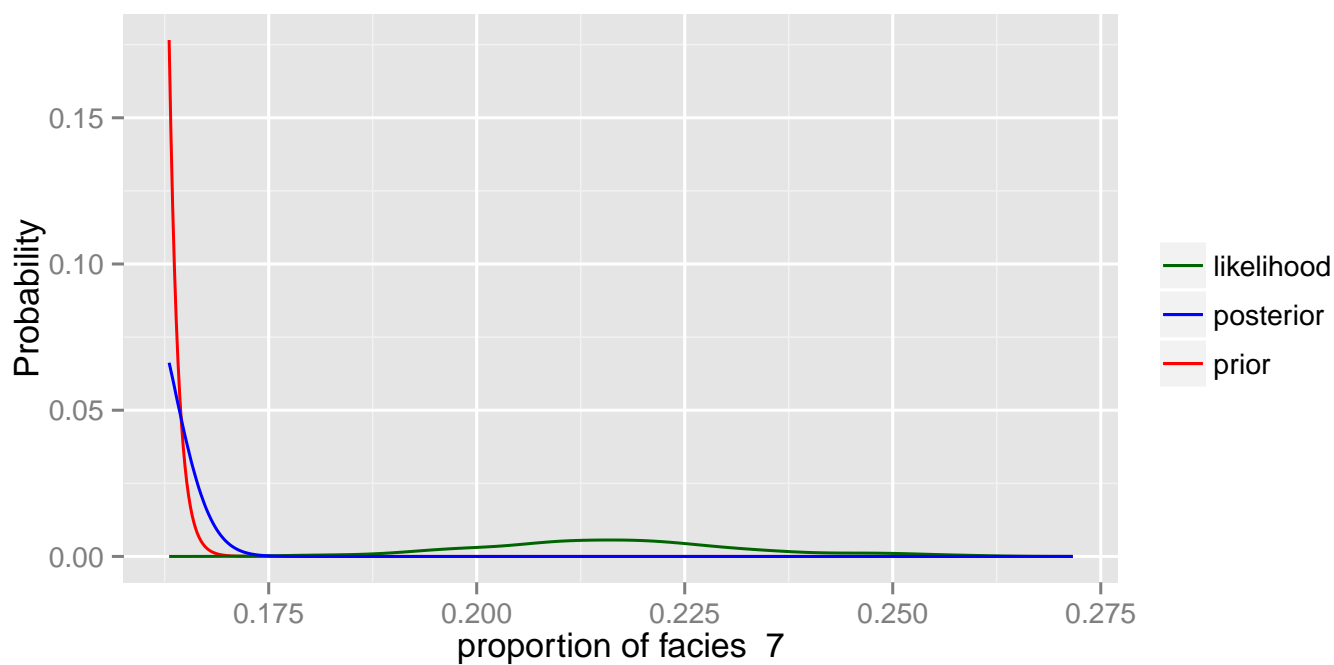


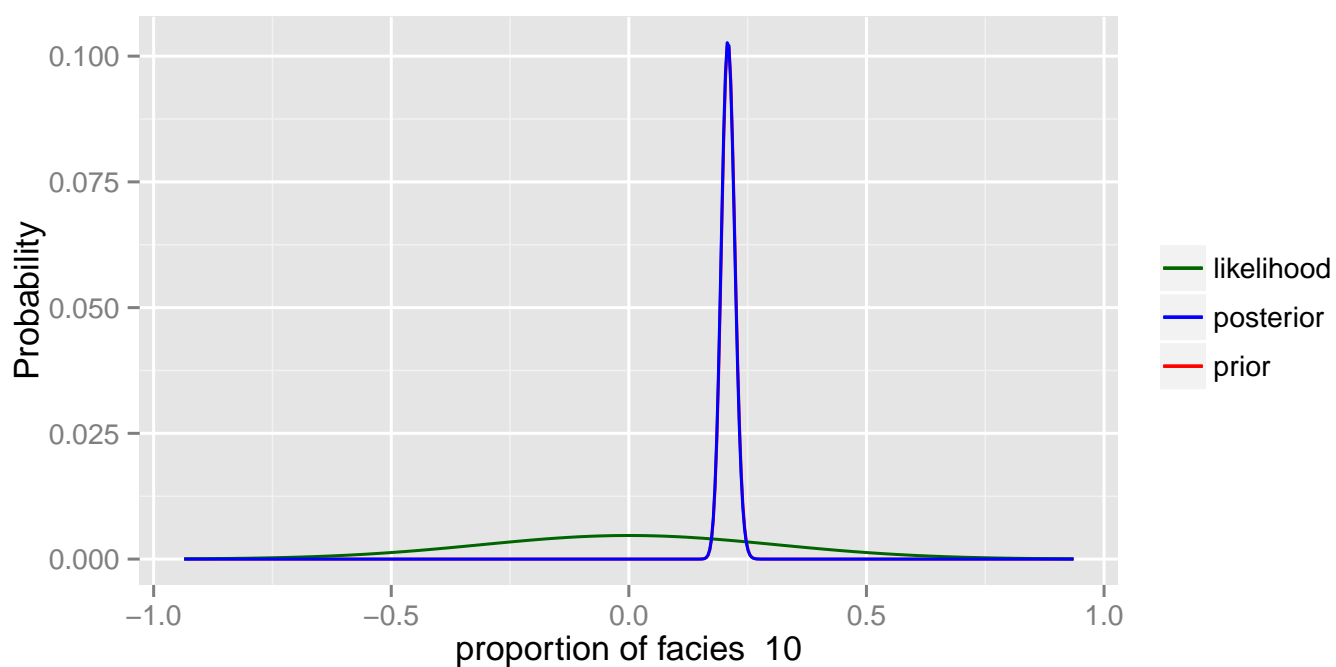
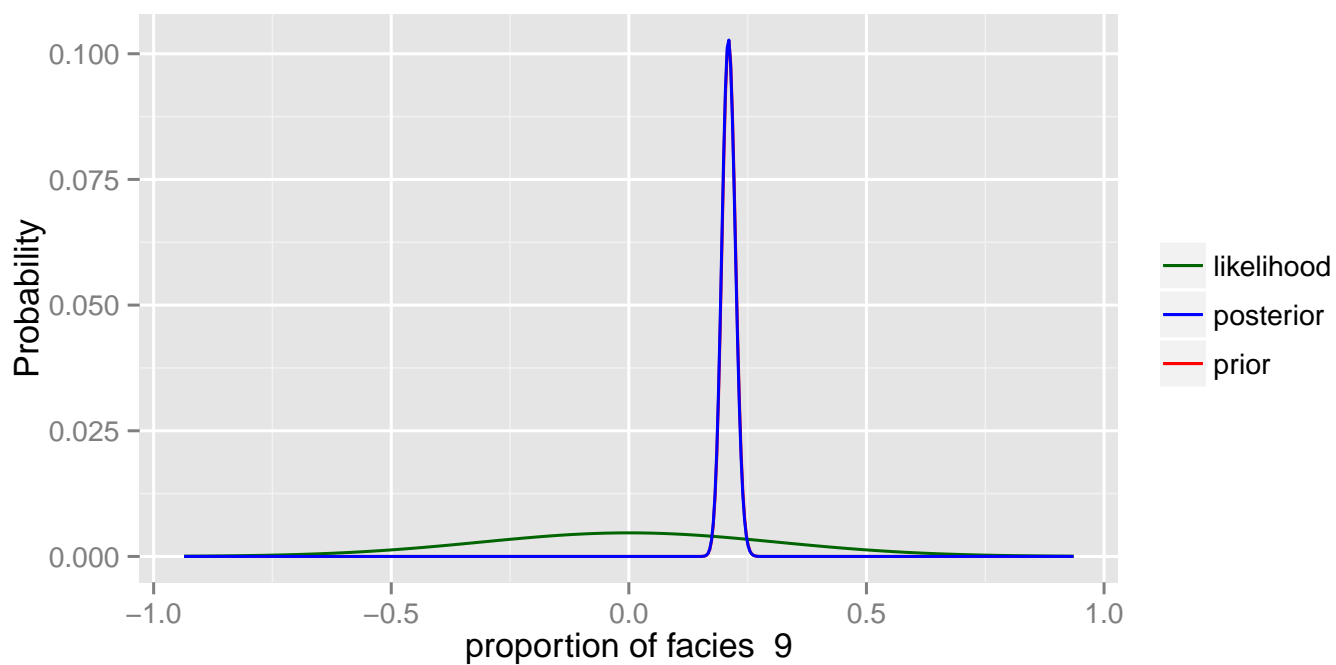
Figure 1.1: we just used linear discriminant analysis instead of logistic regression to plot prediction vs. depth. Posteriors are not used in constructing this figure.











## 2 MARKOV CHAIN AS A STOCHASTIC GRAPH

Various assumptions used for solving this problem are summarized below.

1. For the work over, first arrived well, will be served first.
2. If multiple well damage at the same time, the oldest well(the well that has started the chain sooner) will be worked over first.
3. The reservoir engineer has estimated a value of  $N.true$  for each well. As soon as this value becomes zero (or less), the well is considered depleted and should be abandoned.
4. For constructing violin plot, only drilling risks are taken into consideration and reservoir engineer's prediction ( $N.true$ ) will remain the same for all runs. If desired, this assumption can be easily eliminated.

`SetState.R` contains functions that make small changes to state transitions.

```
#Defining states, costs and state transition functions
rm(list=ls())
source(file.path('/Users/eansar2/Desktop/Geostatistics/TakeHome',
                 'SetState.R'))
costs <- list(Queue=0,Drill=-25,FinishedDrill=0,Complete=-25,Produce=-0.1,
              Shut_in=0,WaitForRig=0,WorkOver=-25,Abandon=-10)
states <- c("Queue","Drill","FinishedDrill","Complete","Produce",
            "Shut_in","WaitForRig","WorkOver","Abandon")
```

Three additional properties (`current.state`, `next.state`, `drilling.flag`) are added to the course notes proposed well objects in order to track them more easily. All wells are in Queue at the beginning (time zero).

```
#Initializing well objects
wells <- vector("list",N.wells)
for (i in 1:N.wells){
  wells[[i]] = list(current.state="Queue",next.state="Queue",
                    t.states=matrix(0,10000,N.states),
                    t.drill=sample(2:6,1,p=c(0,0.25,0.5,0.75,1)),
                    t.this=0,N.believe=runif(1,500,1000),
                    N.true=runif(1,500,1000),q=runif(1,0.5,3),value=0,
                    drilling.flag=FALSE)

  colnames(wells[[i]]$t.states) <- states
}
```

---

**Algorithm 1** Markov Chain

---

```
1: Initialize variables
2: while not all wells abandoned do
3:   for each wells do
4:     if drilling job finished then
5:       Move the well out of drilling state
6:     end if
7:     if drilling is empty and this well is in queue then
8:       Drill this well
9:     end if
10:    if any well is damaged then
11:      Work over the earlier damaged well (oldest if multiple)
12:    end if
13:    Determine the next state of the well
14:  end for
15:  for all wells do
16:    Update the well's current state and adjust it's properties
17:    calculate the profit
18:    calculate N.ture
19:    if N.true<=0 then
20:      flag the well for abandoning
21:    end if
22:    if any well is in wait for rig state then
23:      determine possible workover wells and select only one based on assumptions
24:    end if
25:  end for
26:  time=time+1
27: end while
```

---

Initialize the transition matrix so that all the pathes between states are open at the beginning.

```
#Defining initial transition matrix
trans.prob = matrix(0,nrow=N.states,ncol=N.states,
                    dimnames=list(states,states))
trans.prob = initialize(trans.prob) #initializing transition matrix
```

Drilling.flag shows which well is being drilled. wells.abandoned records the wells that are absorbed.

```
#Initiallizing variables
drilling.flag      = rep(FALSE,N.wells)
wells.abandoned   = rep(FALSE,N.wells)
pos.workover.wells = rep(FALSE,N.wells)
def.N.true.wells   = rep(FALSE,N.wells)
waiting.time       = rep(0,N.wells)
workover.well      = 0
time              = 0
```

It is not necessary, but would be more understandable and sometimes useful, if we calculate the costs and some other paramters in a separate for loop. (i.e. after all wells are moved one step and before the end of the month).

```
#Main loop
while (!all(wells.abandoned)){
  #First for loop
  for (i in 1:N.wells){
    #move wells one time step
    ...
  }
  #Second for loop
  for (i in 1:N.wells){
    #for calculating the costs
    ...
  }
  ...
  wells.abandoned[[i]] = (wells[[i]]$current.state=="Abandon")
  time=time+1
}
```

The next state is sampled between all posible pathes weighted by their probabilities.

```

#select the next state.
pos.next.states <- names(which( trans.prob[current.state,]!=0 ))
prob.next.states <- trans.prob[current.state,pos.next.states]
selected.next.state <- sample(pos.next.states,1,p=prob.next.states)
wells[[i]]$next.state <- selected.next.state

```

Below chunk demonstrates how workover wells are selected.

```

#In the second "for" loop
pos.workover.wells[i]=(wells[[i]]$current.state=="WaitForRig")
waiting.time[i] = as.integer(pos.workover.wells[i])
                  *wells[[i]]$t.this

#Before increasing time step, check for workover wells
if (any(pos.workover.wells))
{
  #First check which wells have arrived at WaitForRig state
  max.waiting.wells = which(waiting.time==
                           max(waiting.time[pos.workover.wells]))

  #If more than one well arrive at the same time, choose the well
  # has started the chain sooner(Oldest well)
  workover.well      = min(max.waiting.wells)
}else{
  workover.well      = 0
}

```

Below chunk is located at the begining of the first for loop to check whether the drilling state is empty.

```

#check if any well is being drilled. If not, the next well can be
#drilled.
for (j in 1:N.wells)
  drilling.flag[j] =wells[[j]]$drilling.flag
if (any(drilling.flag))
  trans.prob <- drill.close(trans.prob) else
  trans.prob <- drill.open(trans.prob)

```

The below code is added for abandoning depleted wells.

```

#If N.true of the well is depleted, abandon that well.
def.N.true.wells[i] = (wells[[i]]$N.true <= 0)
if (def.N.true.wells[i])
  trans.prob <- well.abandon(trans.prob) else
  trans.prob <- well.open(trans.prob)

```

Below code is for moving the well out of the drilling state into the finished drilling state if it's `t.drill` is fulfilled.

```
#If drilling is finished move the well out.
if (sum(wells[[i]]$t.states[, "Drill"])==wells[[i]]$t.drill)
  trans.prob <- Finished.drill.open(trans.prob) else
  trans.prob <- Finished.drill.close(trans.prob)
```

Below chunk should be clear.

```
#WorkOver is only open for one well at time
if (i==workover.well)
  trans.prob <- WorkOver.open(trans.prob) else
  trans.prob <- WorkOver.close(trans.prob)
```

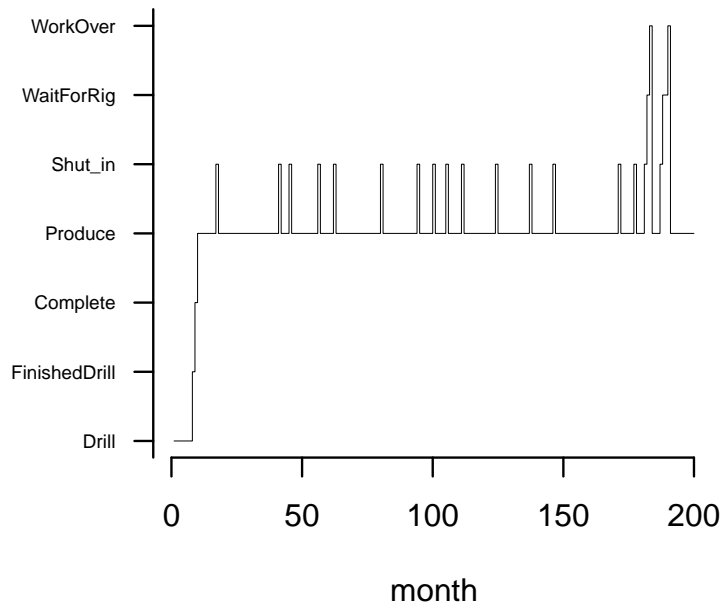
And finally the costs are calculated in the second for loop.

```
#calculate the profit and modify the value of the well
profit=as.integer(wells[[i]]$current.state=="Produce")*wells[[i]]$q
if (!(wells[[i]]$current.state=="Abandon"))
  wells[[i]]$value = (wells[[i]]$value+
                      costs[[wells[[i]]$current.state]]+profit)
#The cost of Abandon state is single time cost.
if ((wells[[i]]$current.state=="Abandon")&&(wells[[i]]$t.this==1))
  wells[[i]]$value = (wells[[i]]$value+
                      costs[[wells[[i]]$current.state]]+profit)
```

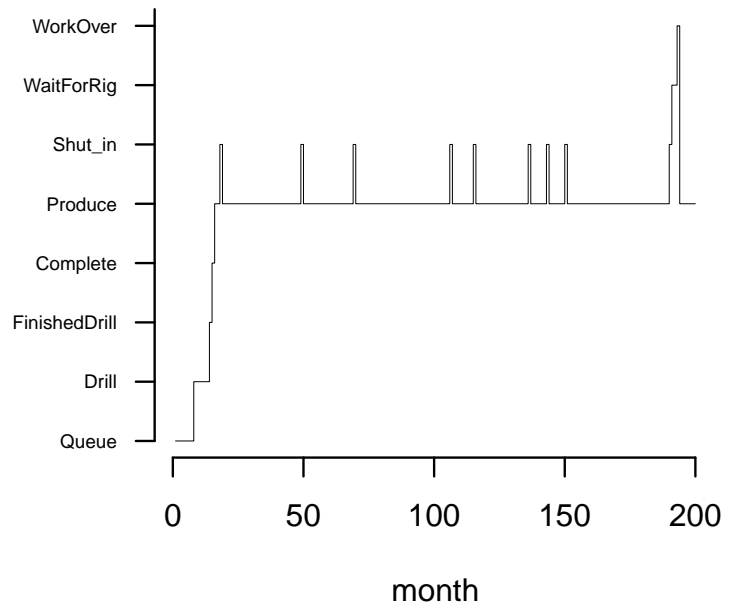
Log of the wells for a prolific field development (revenue of around 2100 million \$ after all wells are abandoned) are shown below. As violen plot indicates this is one of the profitable developments. The average revenue (after 1000 months) is around 600 million \$.



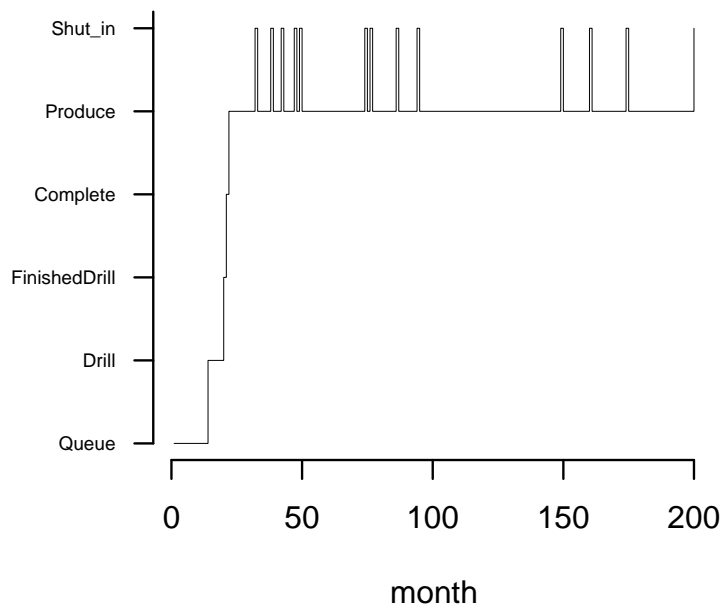
**well 1 log**



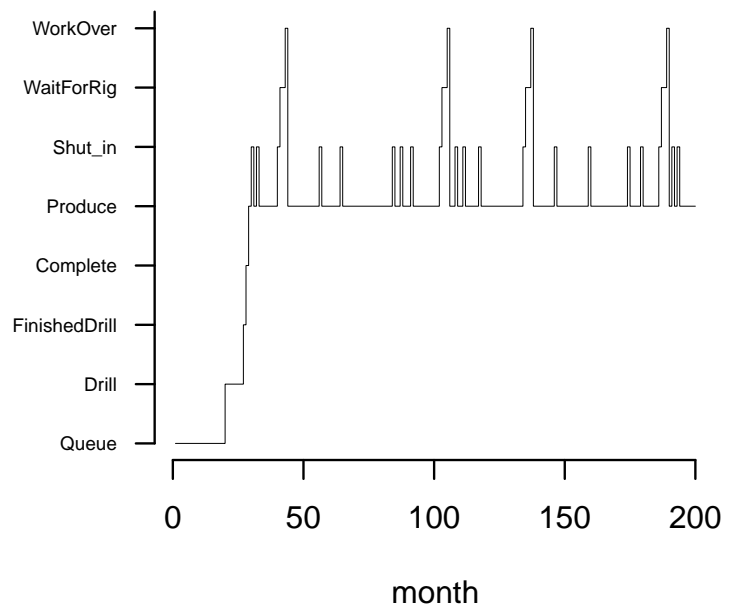
**well 2 log**



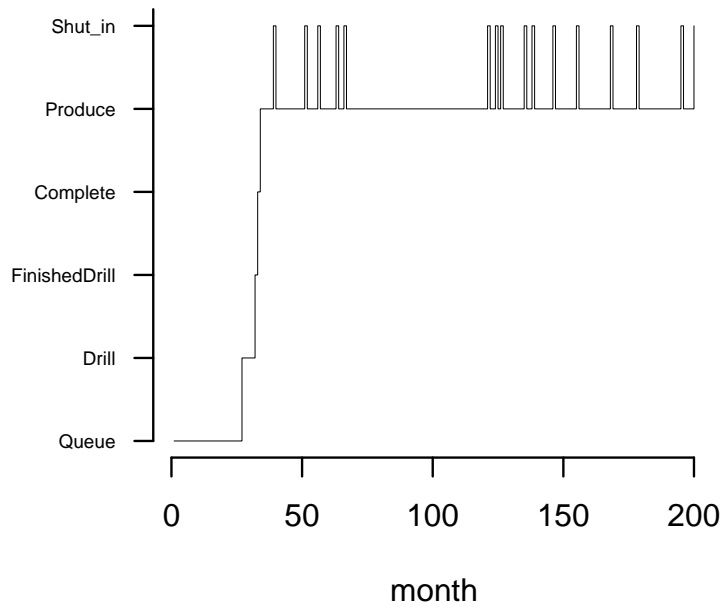
**well 3 log**



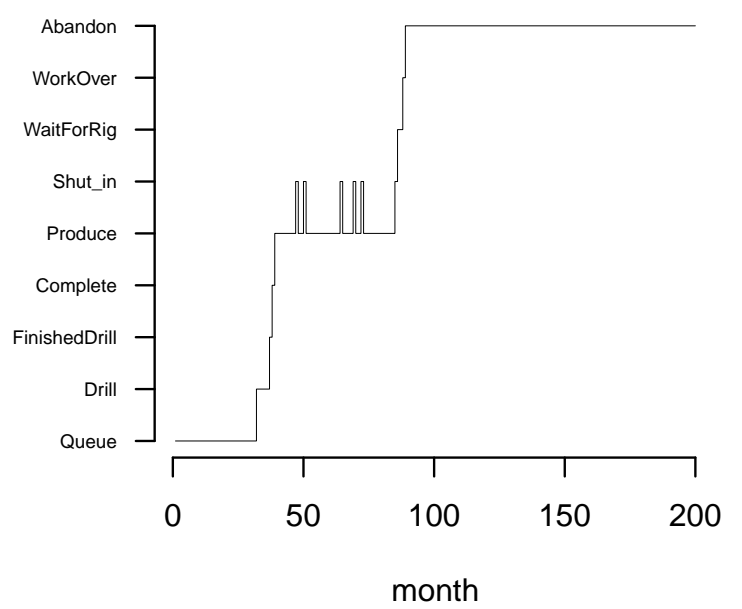
**well 4 log**



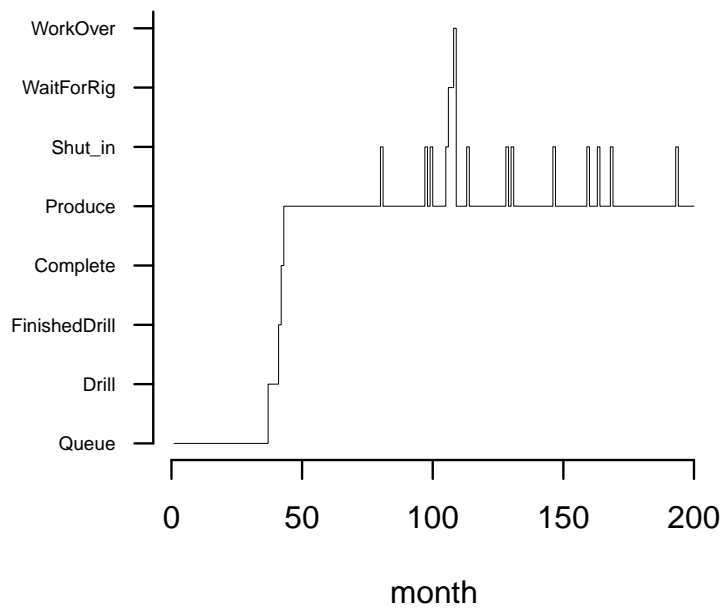
**well 5 log**



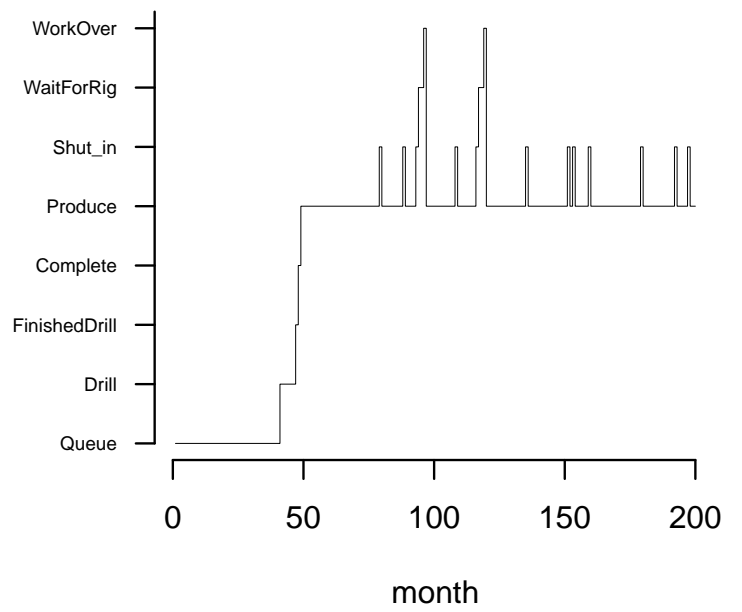
**well 6 log**



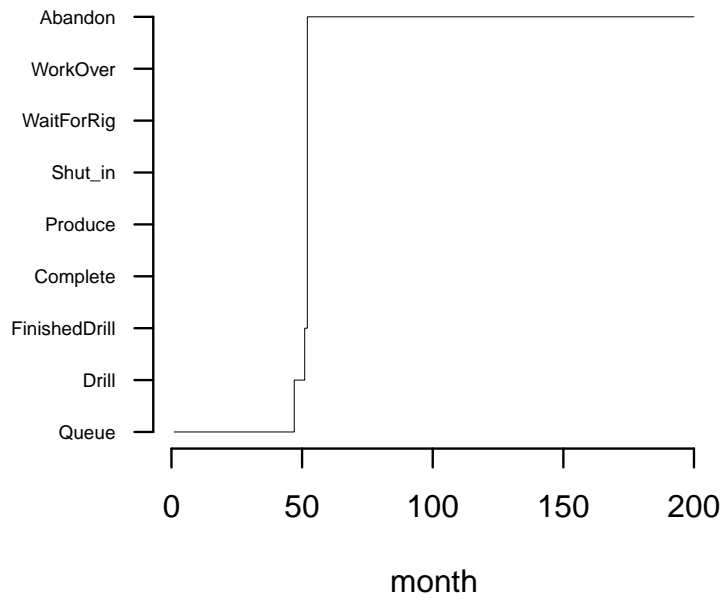
**well 7 log**



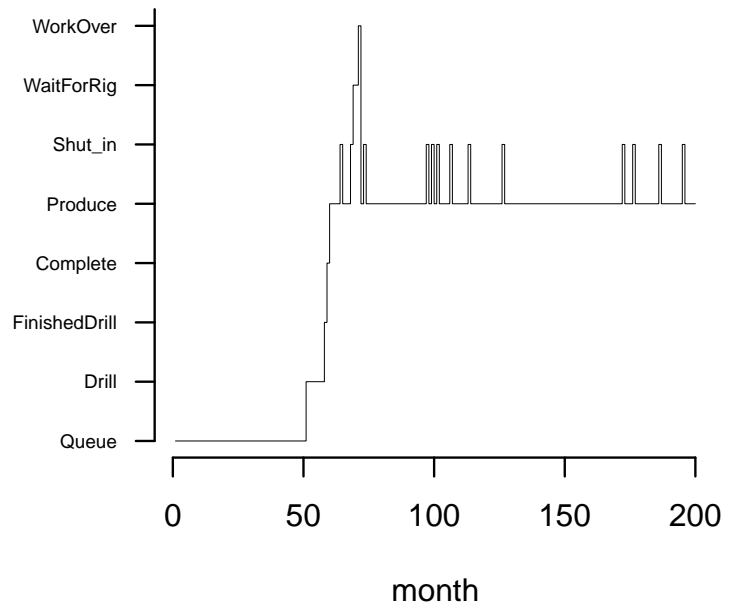
**well 8 log**



**well 9 log**



**well 10 log**



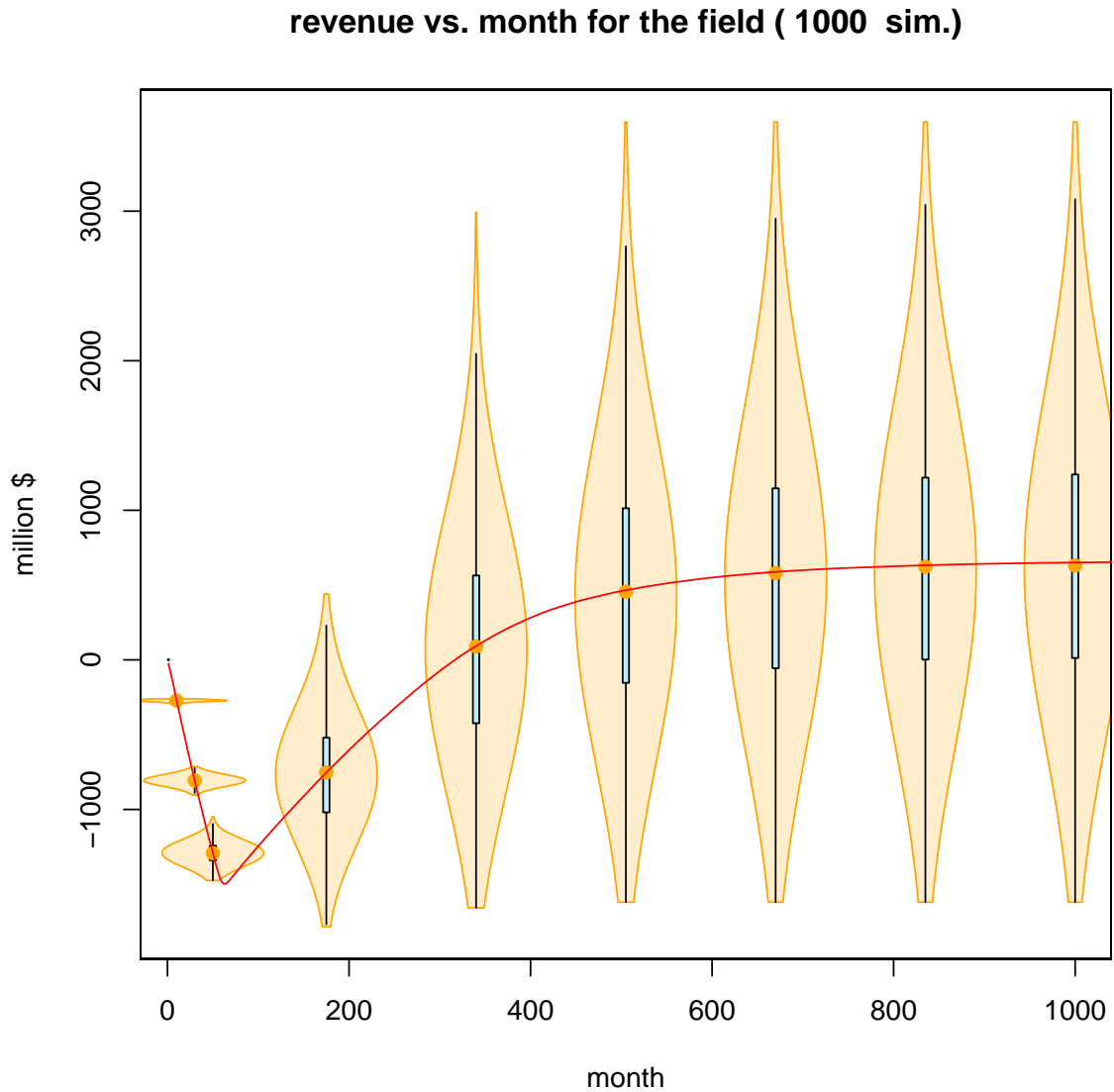


Figure 2.1: Violin plot for the field development. The red line connects the mean of field net revenue calculated after each month. It turns out that the mean is equal to the median. The skewness of the kernell densities for all months are small and upward. It is more likely that we have to wait around 300 months to get our investment money back. If we are the most luckiest person on earth, this waiting time would decrease to 180 months and 3800 million \$ is the maximum revenue we will attain. The most probable maximum cost would be around 1500 million and it happens after around 70 months. The maximum amount that we have to invest on field development does not depend (relatively) on whether we are lucky or not. After a 1000 month!(83 years), the 0.25 percent quantile of violins are roughly higher than zero which can be promising if we are interested in long term revenue.