## HW1

Joe Zhang

```
library(dplyr)
library(ggplot2)
library(mclust)
library(survival)
```

## Problem 5

```
data <- read.csv("~/DataMining/CLV_CRM/cell.csv")</pre>
```

**a**)

It looks like the customers are split evenly across the months and that the customers each month are pretty close to splitting evenly between churn and no churn. According to the crosstable result, we should use stratified sampling method.

```
#data <- cell
table(data[,c('churn','billmonth')])</pre>
```

```
##
        billmonth
## churn Apr 08 Aug 07 Dec 07 FEB 08 JAN 08 Jul 07 Jun 07 Mar 08 May 08
##
            209
                    207
                           246
                                   244
                                          191
                                                  205
                                                         207
                                                                 203
                                                                         207
            205
                    213
                           224
                                          229
                                                                        183
##
       1
                                   191
                                                  194
                                                         217
                                                                 205
##
        billmonth
## churn Nov 07 Oct 07 Sep 07
            206
                    190
                           209
##
       0
##
       1
            203
                    189
                           223
```

b)

2476 people canceled. The retention rate equals 0.02589308.

```
sum(data$churn)

## [1] 2476

r_hat = sum(data$churn,na.rm = TRUE)/sum(data$t2,na.rm = TRUE)
r_hat
```

```
## [1] 0.02589308
```

**c**)

We have to do stratetified sampling. As the retention rate is different across account types or line counts. And the distribution of the value in those two features are not uniform. If we just randomly drwa sample from the dataset, it may give a lot of bias.

d)

The average monthly revenue is 55.7633. E(CLV) = m(1+d)/(1+d-r) = 57.23051

```
mean.rm.na <- function(x){
return(mean(x,na.rm = TRUE))}
function()mean(x,na.rm = TRUE)

## function()mean(x,na.rm = TRUE)

tmp = apply(data[,7:21], 2, mean.rm.na)
m = mean(tmp)
d = 0.01
mean(tmp)

## [1] 55.7633

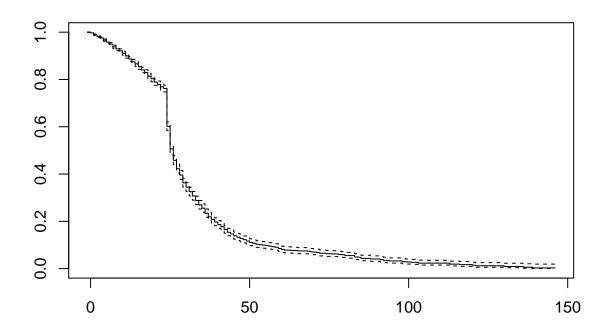
m*(1+d)/(1+d-r_hat)

## [1] 57.23051</pre>
```

**e**)

There is a significant drop at the 23-25 month mark which may indicate that there is a 2 year contract in place.

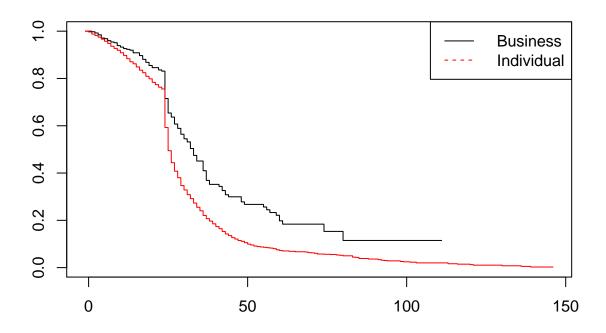
```
fit = survfit(Surv(t2, churn) ~ 1, data=data)
#summary(fit)
plot(fit)
```



f)

The individual is more likely to churn.

```
fit = survfit(Surv(t2, churn) ~ ACCOUNT_TYPE, data=data)
#summary(fit)
plot(fit, col=1:2)
legend("topright", paste(" ",c("Business","Individual")), col=1:2, lty=c(1,2))
```



## $\mathbf{g})$

The fewer lines a customer/business may have, the more likely they will churn. Thos with more lines tend to churn less especially at the 24 month time.

```
data$LINE_COUNT2 = data$LINE_COUNT
data$LINE_COUNT2[data$LINE_COUNT2>5]=5
fit = survfit(Surv(t2, churn) ~ LINE_COUNT2, data=data)
#summary(fit)
#plot(fit)
plot(fit, col=1:6)
legend("topright", paste(" ",c(0,1,2,3,4,5)), col=1:6, lty=c(1,6))
```

