

Assignment 1

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1

a) The correct answer is 0.3 (ii) because since ALQ is MCAR the probability for an observation to be missing is independent of the ALQ value.

$$\Pr(R = 1 \mid ALQ = YES) = \Pr(R = 1 \mid ALQ = NO) = \Pr(R = 1)$$

So, the probability of an observation with ALQ=Yes being missing is the same for when ALQ=No, 0.03.

b) The correct answer is (ii). When ALQ is MAR given gender the probability of an observation being missing changes for different gender values. Gender is assumed to be the only variable affecting the probability of missingness. If gender is adjusted for then the probability of missingness becomes completely at random and independent of what value ALQ takes.

c) The correct answer is (iii). It is not possible to compute a probability for women without knowing the probability of missing values without accounting for gender and the proportions of men and women in the sample.

2

Under a complete case analysis only subjects with all the variables observed are considered. The biggest possible subsample will occur when the missingness occurs for the same subjects along all variables. All variables have a 10% (10 for a sample of 100) of their observations missing. If the 10 subjects with missing values for Y_i are the same than those for Y_j and for all other variables, then there are 10 subjects with missing values and the subsample will contain 90 subjects.

The smallest subsample occurs when the missing values occur for different subjects along all variables. When values missing for Y_i occur for 10 subjects different to the 10 subjects for which variable Y_j is missing and different from all subjects with missing values in any other variables rather than Y_i . If that happens, there would be 100 (10*10) subjects, each with only one missing value. So there would be no complete cases, subsample of 0 subjects.

3

a) $b = 0$ and so missingness in Y_2 depends only on the completely observed variable Y_1 and a random component (Z_3). However, Y_1 and Y_2 are correlated through Z_1 . Small values of Y_1 , which make more probable missingness in Y_2 (because $a(Y_1 - 1)$ becomes negative), are due to negative values in Z_1 . If Z_1 is negative, it is more probable for Y_2 to be smaller (because $2Z_1$ is negative). And so, cases in which Y_2 tends to be smaller relate to cases in which its value tends to be missing.

Looking at the distributios we can see the effect of the relation between the value of Y_2 and missingness. Since observations with higher probability of Y_2 being small are related to higher probability of the value

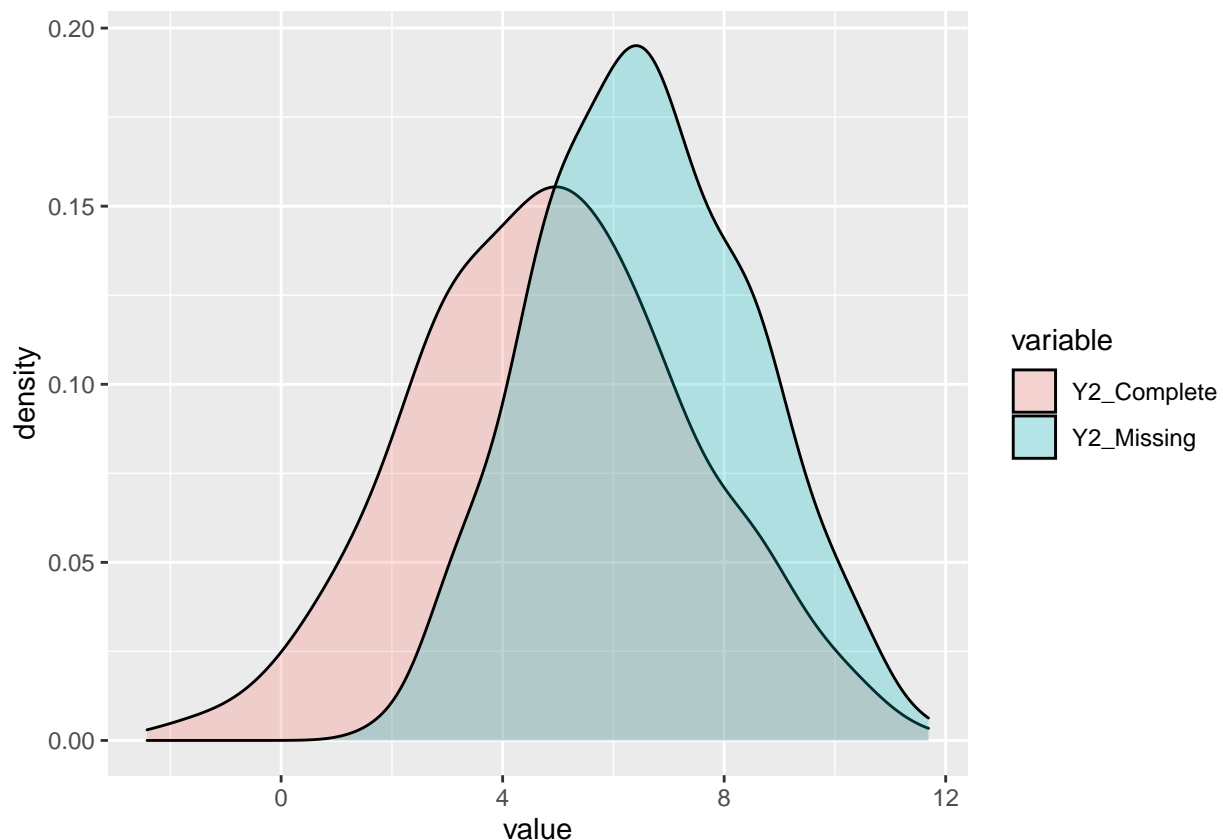
being missing, we can see that the distribution for Y2_Missing is to the right of that for Y2_Complete. For that reason I have decided to classify it as MNAR and not MAR (although MAR would still be ok).

```
library(reshape)
library(ggplot2)
set.seed(29)
mu <- 0; sigma <- 1; a<-2; b<-0;
z1<-rnorm(500,mu,sigma)
z2<-rnorm(500,mu,sigma)
z3<-rnorm(500,mu,sigma)
y1<-1+z1
y2_C<-5+2*z1+z2
y2_M<-ifelse(a*(y1-1)+b*(y2_C-5)+z3 < 0,NA,y2_C)
Disp<- data.frame(Y2_Complete=y2_C,Y2_Missing=y2_M)
Disp<-melt(Disp)
```

```
## Using as id variables
```

```
ggplot(Disp,aes(x=value, fill=variable)) +
  geom_density(alpha=0.25)
```

```
## Warning: Removed 259 rows containing non-finite values (stat_density).
```



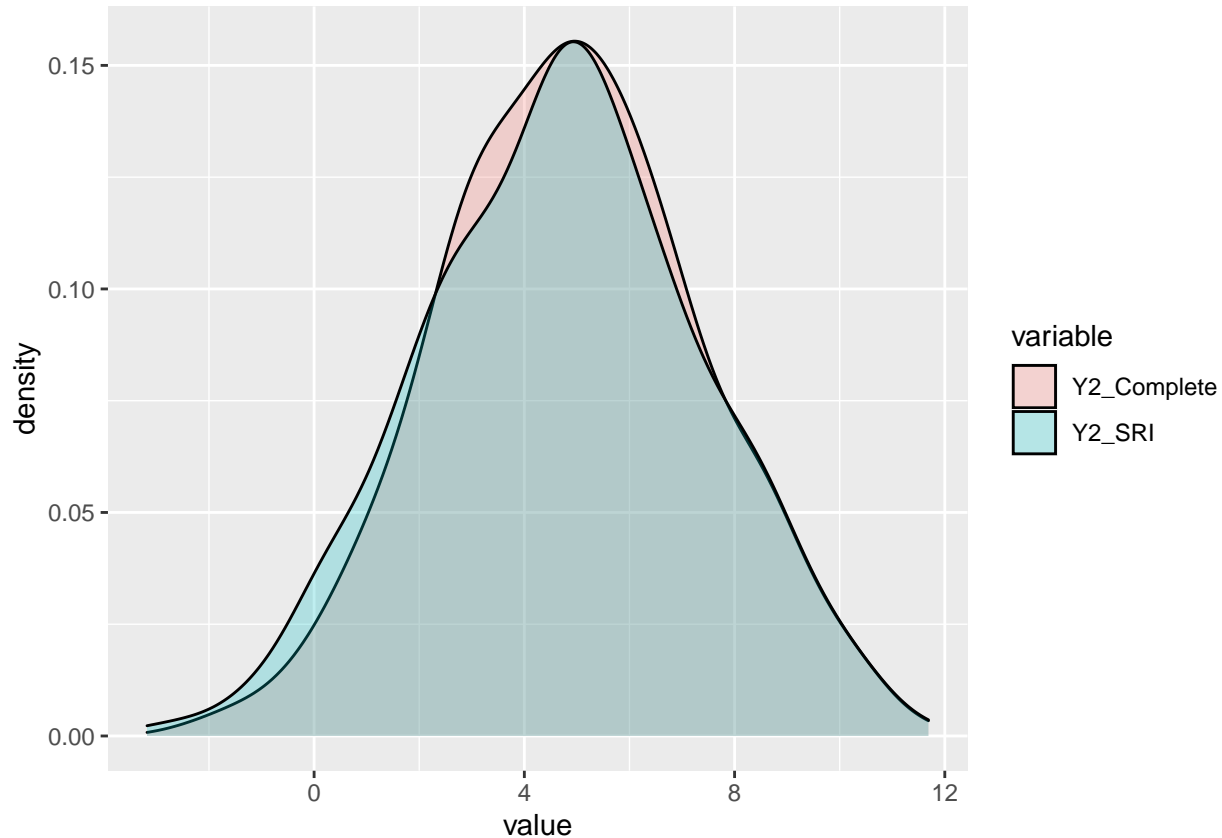
```
fit <- lm(y2_M ~ y1)
sigmaest <- sigma(fit)
pred <- fit$coefficients[1] + y1*fit$coefficients[2] + rnorm(500, 0, sigmaest)
y2_SRI<-ifelse(is.na(y2_M)==TRUE,pred,y2_M)
```

```
Disp2<- data.frame(Y2_Complete=y2_C,Y2_SRI=y2_SRI)
Disp2<-melt(Disp2)
```

b)

```
## Using as id variables
```

```
ggplot(Disp2,aes(x=value, fill=variable)) +
  geom_density(alpha=0.25)
```



The resemblance between both distributions is remarkable. After imputing Y_2 missing values with SRI, the distribution is around the actual mean for complete values. It probably yielded such good results due to the fact that (as stated previously) Y_2 and Y_1 are highly correlated. We see a bit more of variation for smaller values, which makes sense since most of the imputations were needed for smaller values.

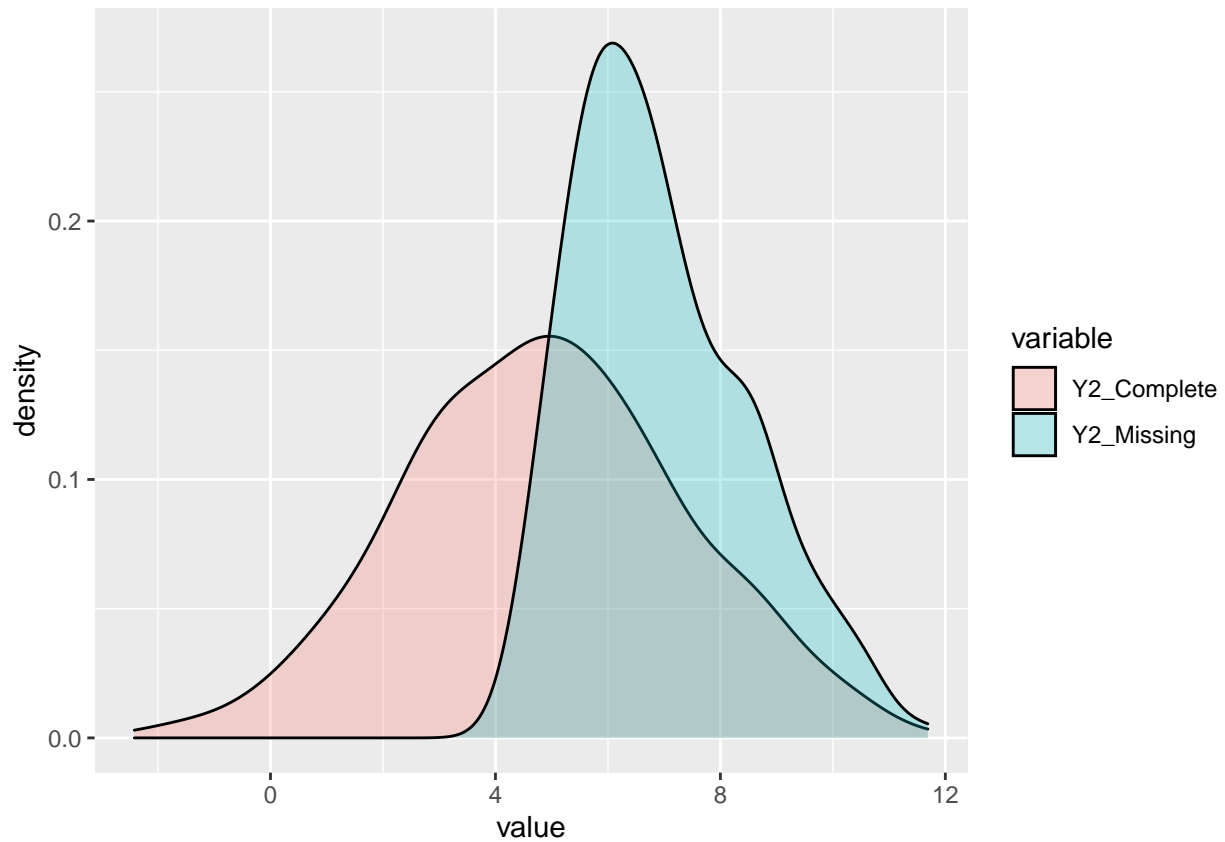
c) In this case $b = 2$ and so missingness in Y_2 depends only on the actual value of Y_2 and a random component (Z_3). It is clear that it is MNAR. Missingness occurs almost entirely for small (> 5) values of Y_2 (because $(Y_2 - 5)$ becomes negative). That is why the missing distribution drops rapidly for values smaller than 5 and is not symmetric.

```
a<-0; b<-2;
y2_M2<-ifelse(a*(y1-1)+b*(y2_C-5)+z3 < 0,NA,y2_C)
Disp3<- data.frame(Y2_Complete=y2_C,Y2_Missing=y2_M2)
Disp3<-melt(Disp3)
```

```
## Using as id variables
```

```
ggplot(Disp3,aes(x=value, fill=variable)) +
  geom_density(alpha=0.25)
```

```
## Warning: Removed 265 rows containing non-finite values (stat_density).
```

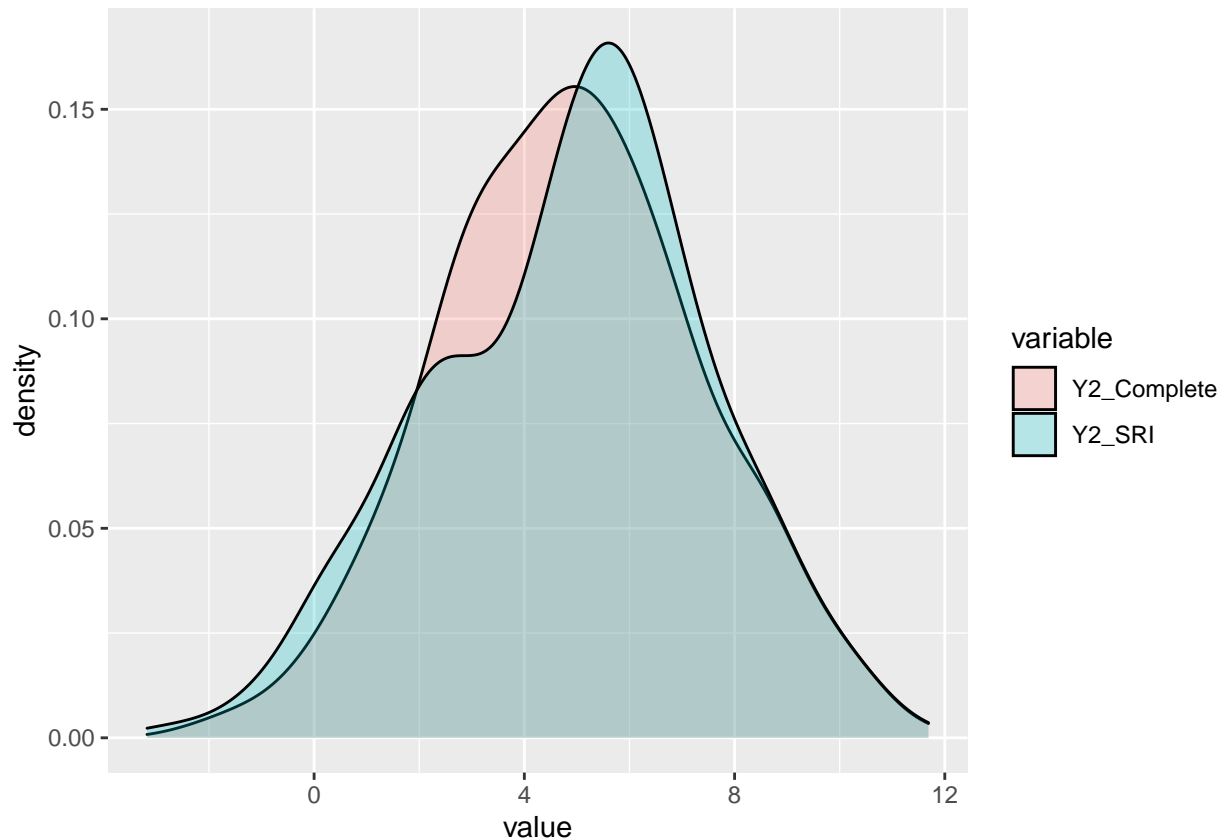


```
fit2 <- lm(y2_M2 ~ y1)
sigmaest2 <- sigma(fit2)
pred2 <- fit2$coefficients[1] + y1*fit2$coefficients[2] + rnorm(500, 0, sigmaest2)
y2_SRI2<-ifelse(is.na(y2_M2)==TRUE,pred,y2_M2)
Disp4<- data.frame(Y2_Complete=y2_C,Y2_SRI=y2_SRI2)
Disp4<-melt(Disp4)
```

d)

```
## Using as id variables
```

```
ggplot(Disp4,aes(x=value, fill=variable)) +
  geom_density(alpha=0.25)
```



Once again, due to the high correlation between Y_1 and Y_2 , SRI does a great job estimating the actual marginal distribution for Y_2 . The distributions are fairly similar and pretty close to each other. Much of the symmetry of the complete distribution is restored.

4

a) Complete Case Analysis

```
load("/cloud/project/databp.Rdata")
ind <- which(is.na(databp$recovtime) == FALSE)
mcc <- mean(databp$recovtime, na.rm = TRUE)
secc <- sd(databp$recovtime, na.rm = TRUE)/sqrt(length(ind))
CorbDose<-cor(databp$logdose[ind],databp$recovtime[ind])
CorbBP<-cor(databp$bloodp[ind],databp$recovtime[ind])
Output<-data.frame(Mean=mcc,SE=secc,Dose_Correlation=CorbDose,Blood_P_Correlation=CorbBP)
Output
```

```
##      Mean      SE Dose_Correlation Blood_P_Correlation
## 1 19.27273 2.603013      0.2391256      -0.01952862
```

b) Mean Imputation

```
recovtimeMI<-ifelse(is.na(databp$recovtime) == TRUE, mcc, databp$recovtime)
mmi <- mean(recovtimeMI)
semi <- sd(recovtimeMI)/sqrt(length(recovtimeMI))
CorbDoseMI<-cor(databp$logdose,recovtimeMI)
CorbBPMI<-cor(databp$bloodp,recovtimeMI)
```

```
Output2<-data.frame(Mean=mmi,SE=semi,Dose_Correlation=CorbDoseMI,Blood_P_Correlation=CorbBPMI)
Output2
```

```
##           Mean           SE Dose_Correlation Blood_P_Correlation
## 1 19.27273 2.284135          0.2150612          -0.01934126
```

The inputted values were:

```
recovtimeMI[is.na(databp$recovtime)==TRUE]
```

```
## [1] 19.27273 19.27273 19.27273
```

c) Mean Regression Imputation

```
fitRecovtime<-lm(recovtime ~ logdose + bloodp, data = databp)
predri <- predict(fitRecovtime,newdata=databp)
recovtimeMRI<-ifelse(is.na(databp$recovtime) == TRUE, predri, databp$recovtime)
mri <- mean(recovtimeMRI)
semri <- sd(recovtimeMRI)/sqrt(length(recovtimeMRI))
CorbDoseMRI<-cor(databp$logdose,recovtimeMRI)
CorbBPMRI<-cor(databp$bloodp,recovtimeMRI)
Output3<-data.frame(Mean=mri,SE=semri,Dose_Correlation=CorbDoseMRI,Blood_P_Correlation=CorbBPMRI)
Output3
```

```
##           Mean           SE Dose_Correlation Blood_P_Correlation
## 1 19.44428 2.312845          0.2801835          -0.0111364
```

The inputted values were:

```
predri[is.na(databp$recovtime)==TRUE]
```

```
##           4           10           22
## 14.26254 21.51562 26.32896
```

d) Stochastic Regression Imputation

In this case we need to be careful, because due to the stochastic component we could get a negative value for the recovery time. And of course, a negative recovery time makes no sense. With the coefficients obtained, the sigma from the regression and the seed set we have no negative value and no further adjustment is needed.

```
set.seed(29)
predsri <- predict(fitRecovtime,newdata=databp)+ rnorm(length(databp$recovtime),0,sigma(fitRecovtime))
recovtimeSRI<-ifelse(is.na(databp$recovtime) == TRUE, predsri, databp$recovtime)
msri <- mean(recovtimeSRI)
sesri <- sd(recovtimeSRI)/sqrt(length(recovtimeSRI))
CorbDoseSRI<-cor(databp$logdose,recovtimeSRI)
CorbBPSRI<-cor(databp$bloodp,recovtimeSRI)
Output4<-data.frame(Mean=msri,SE=sesri,Dose_Correlation=CorbDoseSRI,Blood_P_Correlation=CorbBPSRI)
Output4
```

```
##           Mean           SE Dose_Correlation Blood_P_Correlation
## 1 21.53037 2.724354          0.3604275          0.02389744
```

The inputted values were:

```
predsri[is.na(databp$recovtime)==TRUE]
```

```
##          4          10          22
## 25.86518 35.13001 53.26402
```

e) Predictive Mean Matching

```
recovtimePMM<-databp$recovtime
for (i in which(is.na(recovtimePMM) == TRUE)){
  ini_pred<-predri[i]
  dif<-ini_pred^2
  for (j in which(is.na(databp$recovtime) == FALSE)){
    if((ini_pred-predri[j])^2<dif){dif<-(ini_pred-predri[j])^2;recovtimePMM[i]<-recovtimePMM[j]}
  }
}
mpmm <- mean(recovtimePMM)
sepmm <- sd(recovtimePMM)/sqrt(length(recovtimePMM))
CorbDosePMM<-cor(databp$logdose,recovtimePMM)
CorbBPPMM<-cor(databp$bloodp,recovtimePMM)
Output4<-data.frame(Mean=mpmm,SE=sepmm,Dose_Correlation=CorbDosePMM,Blood_P_Correlation=CorbBPPMM)
Output4
```

```
##      Mean      SE Dose_Correlation Blood_P_Correlation
## 1 19.44 2.464467      0.3037945      -0.03208685
```

The inputted values were:

```
recovtimePMM[is.na(databp$recovtime)==TRUE]
```

```
## [1] 13 10 39
```

f) It is less dependent on linearity assumptions. It is better at dealing with issues such as heteroscedasticity because it uses real values from other subjects and that helps to account for variance changes.

The main problem that I can think of for this method is that it can happen that many predictions for missing values are closest to the same predicted value of the donor. That could cause for the same value to be inputted multiple times. So it may lead to biased estimations and of course to underestimation of the standard errors.

Github Repository:

<https://github.com/Arturo-Esquivel/Incomplete-Data-Analysis>