Data wrangling

Banana

Data Cleaning

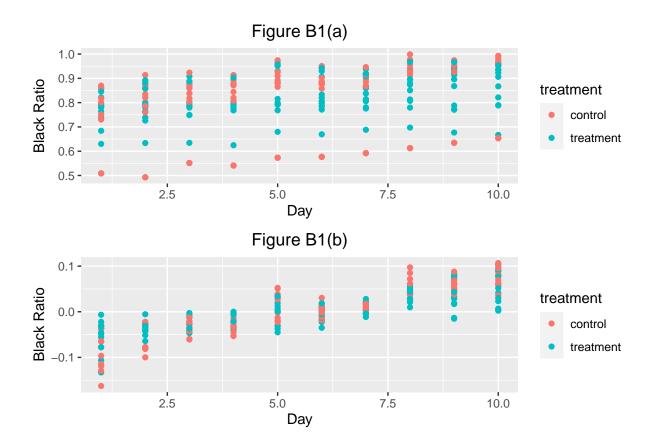
- Figure B1(a) indicates there exists both individual fixed effect (i.e., value that varies among differnt subjects, but fixed over time) and block effect (i.e., value that varies between blocks but fixed within blocks)
- The individual fixed effect could have caused by how the picture was taken by different individuals and block fixed effect could have been the result of different environmental condition (i.e., temperature of the house or humidity or lighting).
- The individual and block fixed had been taken out in Figure B1(b)

```
#remove the fixed effect
d[,b_mu:=mean(black_ratio), by = .(block,banana_number)]
d[,y := black_ratio - b_mu]

p1 <- d %>% ggplot(aes(x = day, y = black_ratio)) +
    geom_point(aes(color = treatment)) + ggtitle("Figure B1(a)") +
    xlab("Day") + ylab("Black Ratio") + theme(plot.title = element_text(hjust = 0.5))

p2 <- d %>% ggplot(aes(x = day, y = y)) +
    geom_point(aes(color = treatment)) + ggtitle("Figure B1(b)") +
    xlab("Day") + ylab("Black Ratio") + theme(plot.title = element_text(hjust = 0.5))

p1 / p2
```



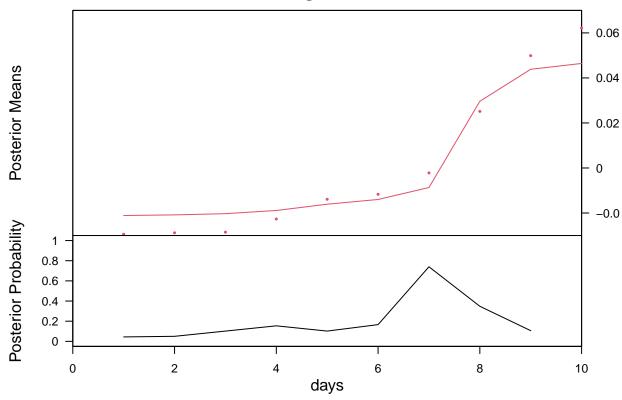
- The percent of black-ratio should be non-decreasing function of days, but we have noticed that black_ratio can decrease when the tip of the banana withers which cause size of the banana cropped during the image processing part.
- To account for such error introduced while measuring the black_ratio, one of off-line abrupt change detection algorithm was employeed to detect changes in blac_ratio while accounting for such small noise.

Estimate the treatment effect

• The response is the day at which rapid deteroriation of banana condition was observed and the following figure shows there were detected

Code for mannual confirmation

Figure B2



```
invisible(capture.output(bcp_sum <- as.data.frame(summary(bcp_x))))

bcp_sum$id <- 1:length(dg)
#selecting draft_number with posterior probability greater than 0.2
sel <- as.data.frame(bcp_sum[which(bcp_x$posterior.prob > 0.2), ])
sel <- sel[sel$id <9,]
sel <- sel[which.max(sel$Probability),]
#get the id
time_of_change <- time(dg)[sel$id]
time_of_change[1]</pre>
```

[1] 7

Get the data

```
{
  start <- 1 + (val-1)*10
  end <- (10*val)
  #get the subject information
  val_block <- db[start,block]
  val_subject <- db[start,banana_number]
  val_treat <- db[start,treatment]

# # print(paste(start,":",end))
  d_temp <- db[start:end,]
  d_turn <- getChangeDate(d_temp)
  b_result[val,] <- c(val_block,val_subject,val_treat,d_turn)
}

# b_result</pre>
```

Analysis

We have used block random assignement design.

We have three blocks, B, N, and J and the probability of assignment to treatment, p(d=1) = 0.5 for all three which allows us to later pool the data across the block and estimate ATE (page 76 FE)

We have selected block radomization to reduce sampling variablity (see page 72 FE). The subjects within the group are from the same brunch LINK such that subjects in each block have similiar potential outcomes. This also ensured that certain subgroups are available for seperate analysis (see page 71 FE)

Sharp null hypothesis

We began by testing sharp null hypothesis of no treatment effect

the treatment effect was measured by the day beyond which the black ratio rapidly increased.

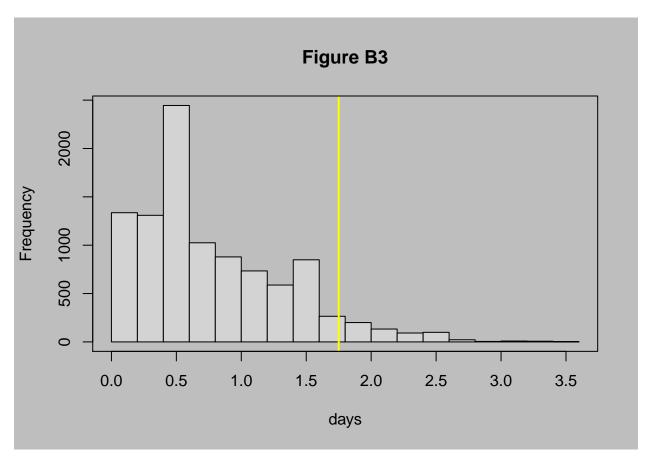
```
#get control and treatment data
b_control <- as.integer(b_result[b_result[,"treatment"] == "control","d_turn"])
b_treatment <- as.integer(b_result[b_result[,"treatment"] == "treatment","d_turn"])

#put them into a vector
Z <- c(b_control,b_treatment)

#get the length of each vectors
n <- length(b_control)
m <- length(b_treatment)
N <- length(Z)

# Number of permutations
K = 10000</pre>
# Test statistic
```

```
getMean <- function(A,B) abs(mean(A) - mean(B))</pre>
# Test statistic for the observed sample
b_mean <- getMean(b_control,b_treatment)</pre>
# Vector of test statistics for each permutation
TT <- vector()
# Permutation test
for(i in 1:K){
 #set.seed(i)
Z.pi <- sample(Z, N, replace = FALSE)</pre>
TT[i] <- getMean(Z.pi[1:n], Z.pi[(n+1):(n+m)])</pre>
# Visualising the permuted test statistics
par(bg = 'grey')
hist(TT,main="Figure B3",
        xlab="days",
        ylab="Frequency")
abline(v = b_mean , lwd = 2, col = "yellow")
box()
```



```
# approximate p-value
b_pvalue <- mean(TT>b_mean )
```

The p-value associated with the observed statistic is 0.057.

Regression Estimator for Block Randomization

We have 3 blocks, B, N, and J with 8 samples in each block.

```
mod_b <- lm(d_turn ~ treatment + as.factor(block), data = b_result)</pre>
coeftest(mod_b, vcov = vcovHC(mod_b, type = "HC1"))
##
## t test of coefficients:
##
                     Estimate Std. Error t value Pr(>|t|)
##
                                 0.64013 4.6824 0.0001432 ***
## (Intercept)
                      2.99733
## treatment 1.50535
                                 0.79142 1.9021 0.0716616 .
## as.factor(block)J -0.22193
                                 1.05018 -0.2113 0.8347748
                                 0.76663 3.5400 0.0020553 **
## as.factor(block)N
                      2.71390
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
b_result %>% ggplot(aes(x = d_turn, fill=treatment)) + geom_bar() + facet_wrap(~block,ncol = 1)+ ggtit
 xlab("Day") + ylab("Count") + theme(plot.title = element_text(hjust = 0.5))
```



