# SampleSplitting

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```
library(dplyr)
## Warning: package 'dplyr' was built under R version 4.2.3
##
## Attaching package: 'dplyr'
## The following objects are masked from 'package:stats':
##
##
       filter, lag
## The following objects are masked from 'package:base':
##
##
       intersect, setdiff, setequal, union
library(ggplot2)
## Warning: package 'ggplot2' was built under R version 4.2.3
library(tidyr)
## Warning: package 'tidyr' was built under R version 4.2.3
```

# Setting 1: CRE, splitting by treatment and conditions with no-harm calibration

```
# set up a CRE
set.seed(2025)
MC = 1000
split_setting = c(0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8)
# num_models = 2

n1 = 300
n0 = 300
n = n1 + n0

# generate data
X1 = rnorm(n)
X2 = rnorm(n)
Y0 = rpois(n, lambda = exp(0.5 * X1 + 0.5 * X2))
Y1 = rpois(n, lambda = exp(0.3 * X1 + 0.4 * X2))
# true effect
```

```
tau = mean(Y1 - Y0)
result_correct_model = lapply(1:length(split_setting),
                              function (x){
                                data.frame(
                                  tau = rep(0, MC),
                                  tau_hat_0 = rep(0, MC),
                                  var_hat_0 = rep(0, MC),
                                  tau_hat_cf = rep(0, MC),
                                  var_hat_cf = rep(0, MC)
                                )
                              })
result_wrong_model = lapply(1:length(split_setting),
                            function (x){
                              data.frame(
                                tau = rep(0, MC),
                                tau_hat_0 = rep(0, MC),
                                var_hat_0 = rep(0, MC),
                                tau_hat_cf = rep(0, MC),
                                var_hat_cf = rep(0, MC)
                            })
set.seed(2024)
for (split_index in 1:length(split_setting)){
  print(paste0("split_index: ", split_index))
 pb = txtProgressBar(min = 0, max = MC, initial = 0)
  for (iter in 1:MC){
  setTxtProgressBar(pb, iter)
  # observed data
 Z = sample(c(rep(1, n1), rep(0, n0)))
 Y = Z * Y1 + (1 - Z) * Y0
  # Without calibration
  tau hat 0 = sum(Y[Z==1])/n1 - sum(Y[Z==0])/n0
  var_hat_0 = var(Y[Z==1])/n1 + var(Y[Z==0])/n0
  # With splitting and calibration
 na = 300
 nb = 300
 na1 = na * split_setting[split_index]
 nb1 = n1 - na1
 na0 = na - na1
 nb0 = nb - nb1
 S1 = sample(c(rep("a", na1), rep("b", nb1)), size = n1)
 S0 = sample(c(rep("a", na0), rep("b", nb0)), size = n0)
 S = rep(NA, n)
 S[Z == 1] = S1
 S[Z == 0] = S0
```

```
full data = data.frame(
 Y = Y
 Z = Z,
 X1 = X1
 X2 = X2
 S = S
full_data_cf = full_data
# Model fitting with Sample "a" and "b"
glm_fit_a1 = glm(Y~X1+X2, data = full_data%%filter(S=="a" & Z==1), family = "poisson")
glm_fit_a0 = glm(Y~X1+X2, data = full_data%%filter(S=="a" & Z==0), family = "poisson")
glm_fit_b1 = glm(Y~X1+X2, data = full_data%%filter(S=="b" & Z==1), family = "poisson")
glm_fit_b0 = glm(Y~X1+X2, data = full_data%%filter(S=="b" & Z==0), family = "poisson")
\# qlm_fit_a1 = qlm(Y\sim X1, data = full_data\% > \% filter(S=="a" & Z==1), family = "poisson")
\# \ glm\_fit\_a0 = glm(Y\sim X1, \ data = full\_data\% > \% filter(S=="a" \ \& \ Z==0), \ family = "poisson")
\# glm\_fit\_b1 = glm(Y\sim X1, data = full\_data\%>\% filter(S=="b" \& Z==1), family = "poisson")
# qlm \ fit \ b0 = qlm(Y\sim X1, \ data = full \ data%>% filter(S=="b" & Z==0), \ family = "poisson")
pred_a1_of = predict(glm_fit_a1, newdata = full_data%/filter(S=="a"), type = "response")
pred_a0_of = predict(glm_fit_a0, newdata = full_data%/filter(S=="a"), type = "response")
pred_b1_of = predict(glm_fit_b1, newdata = full_data%>%filter(S=="b"), type = "response")
pred_b0_of = predict(glm_fit_b0, newdata = full_data%/filter(S=="b"), type = "response")
pred1 = rep(NA, n)
pred0 = rep(NA, n)
pred1[S=="a"] = pred_a1_of
pred0[S=="a"] = pred_a0_of
pred1[S=="b"] = pred_b1_of
pred0[S=="b"] = pred_b0_of
full_data = cbind(full_data, pred1, pred0)
## Prediction based on cross fitting
pred_a1_cf = predict(glm_fit_b1, newdata = full_data%/filter(S=="a"), type = "response")
pred a0 cf = predict(glm fit b0, newdata = full data%>%filter(S=="a"), type = "response")
pred_b1_cf = predict(glm_fit_a1, newdata = full_data%/filter(S=="b"), type = "response")
pred_b0_cf = predict(glm_fit_a0, newdata = full_data%/filter(S=="b"), type = "response")
pred1 = rep(NA, n)
pred0 = rep(NA, n)
pred1[S=="a"] = pred_a1_cf
pred0[S=="a"] = pred_a0_cf
pred1[S=="b"] = pred_b1_cf
pred0[S=="b"] = pred_b0_cf
full_data_cf = cbind(full_data_cf, pred1, pred0)
# Linear calibration for the model
lm_fit_a1 = lm(Y~pred1+pred0, data = full_data %>% filter(S == "a" & Z == 1))
lm_fit_a0 = lm(Y~pred1+pred0, data = full_data %% filter(S == "a" & Z == 0))
lm_fit_b1 = lm(Y~pred1+pred0, data = full_data %% filter(S == "b" & Z == 1))
```

```
lm_fit_b0 = lm(Y~pred1+pred0, data = full_data %% filter(S == "b" & Z == 0))
 # Cross fit based on linear calibration
 pred_a1_cf_lc = predict(lm_fit_b1, newdata = full_data_cf%>%filter(S == "a"))
 pred_a0_cf_lc = predict(lm_fit_b0, newdata = full_data_cf%%filter(S == "a"))
 pred_b1_cf_lc = predict(lm_fit_a1, newdata = full_data_cf%/%filter(S == "b"))
 pred_b0_cf_lc = predict(lm_fit_a0, newdata = full_data_cf%%filter(S == "b"))
 pred1_lc = rep(NA, n)
 pred0_lc = rep(NA, n)
 pred1_lc[S == "a"] = pred_a1_cf_lc
 pred0_lc[S == "a"] = pred_a0_cf_lc
 pred1_lc[S == "b"] = pred_b1_cf_lc
 pred0_lc[S == "b"] = pred_b0_cf_lc
 full_data_cf = cbind(full_data_cf, pred1_lc, pred0_lc)
 ## getting residuals
 full_data_cf = full_data_cf %>%
   mutate(epsilon = case_when(
     Z == 1 \sim Y - pred1_lc,
     Z == 0 \sim Y - pred0_lc
   ))
 # Construct estimator
 ## point estimator
 mu_cf_a1 = 1/na * sum(full_data_cf$epsilon[S=="a" & Z==1])/(na1/na) + 1/na * sum(pred1_lc[S=="a"])
 mu_cf_a0 = 1/na * sum(full_data_cf$epsilon[S=="a" & Z==0])/(na0/na) + 1/na * sum(pred0_lc[S=="a"])
 mu_cf_b1 = 1/nb * sum(full_data_cf$epsilon[S=="b" & Z==1])/(nb1/nb) + 1/nb * sum(pred1_lc[S=="b"])
 tau_hat_cf = na/n * (mu_cf_a1-mu_cf_a0) + nb/n * (mu_cf_b1-mu_cf_b0)
 var_hat_cf =
   na^2/n^2 * (var(full_data_cf$epsilon[S=="a" & Z==1])/na1 + var(full_data_cf$epsilon[S=="a" & Z==0])
   nb^2/n^2 * (var(full_data_cf$epsilon[S=="b" & Z==1])/nb1 + var(full_data_cf$epsilon[S=="b" & Z==0])
 result_correct_model[[split_index]]$tau[iter] = tau
 result_correct_model[[split_index]]$var_hat_0[iter] = var_hat_0
 result_correct_model[[split_index]]$tau_hat_cf[iter] = tau_hat_cf
 result_correct_model[[split_index]] \square_hat_cf[iter] = var_hat_cf
}
close(pb)
}
## [1] "split_index: 1"
## [1] "split_index: 2"
## ========
## [1] "split_index: 3"
## ==========
## [1] "split_index: 4"
## [1] "split_index: 5"
```

```
## [1] "split_index: 6"
## -----
## [1] "split_index: 7"
## -----
set.seed(2024)
for (split_index in 1:length(split_setting)){
 print(paste0("split_index: ", split_index))
 pb = txtProgressBar(min = 0, max = MC, initial = 0)
 for (iter in 1:MC){
 setTxtProgressBar(pb, iter)
 # observed data
 Z = sample(c(rep(1, n1), rep(0, n0)))
 Y = Z * Y1 + (1 - Z) * Y0
 # Without calibration
 tau_hat_0 = sum(Y[Z==1])/n1 - sum(Y[Z==0])/n0
 var_hat_0 = var(Y[Z==1])/n1 + var(Y[Z==0])/n0
 # With splitting and calibration
 na = 300
 nb = 300
 na1 = na * split setting[split index]
 nb1 = n1 - na1
 na0 = na - na1
 nb0 = nb - nb1
 S1 = sample(c(rep("a", na1), rep("b", nb1)), size = n1)
 S0 = sample(c(rep("a", na0), rep("b", nb0)), size = n0)
 S = rep(NA, n)
 S[Z == 1] = S1
 S[Z == 0] = S0
 full_data = data.frame(
   Y = Y
   Z = Z
   X1 = X1
   X2 = X2
   S = S
 full_data_cf = full_data
 # Model fitting with Sample "a" and "b"
 \# \ glm\_fit\_a1 = glm(Y\sim X1+X2, \ data = full\_data\%>\% filter(S=="a" \ \& Z==1), \ family = "poisson")
 \# qlm_fit_a0 = qlm(Y\sim X1+X2, data = full_data\%\% filter(S=="a" & Z==0), family = "poisson")
  \# \ glm\_fit\_b1 = glm(Y\sim X1+X2, \ data = full\_data\%>\% filter(S=="b" \& Z==1), \ family = "poisson") 
 \# glm\_fit\_b0 = glm(Y\sim X1+X2, data = full\_data\%)\% filter(S=="b" & Z==0), family = "poisson")
 glm_fit_a1 = glm(Y~X1, data = full_data%>%filter(S=="a" & Z==1), family = "poisson")
```

```
glm_fit_a0 = glm(Y~X1, data = full_data%>%filter(S=="a" & Z==0), family = "poisson")
glm_fit_b1 = glm(Y~X1, data = full_data%>%filter(S=="b" & Z==1), family = "poisson")
glm_fit_b0 = glm(Y~X1, data = full_data%>%filter(S=="b" & Z==0), family = "poisson")
pred_a1_of = predict(glm_fit_a1, newdata = full_data%/filter(S=="a"), type = "response")
pred_a0_of = predict(glm_fit_a0, newdata = full_data%/filter(S=="a"), type = "response")
pred_b1_of = predict(glm_fit_b1, newdata = full_data%/filter(S=="b"), type = "response")
pred_b0_of = predict(glm_fit_b0, newdata = full_data%/filter(S=="b"), type = "response")
pred1 = rep(NA, n)
pred0 = rep(NA, n)
pred1[S=="a"] = pred_a1_of
pred0[S=="a"] = pred a0 of
pred1[S=="b"] = pred_b1_of
pred0[S=="b"] = pred_b0_of
full_data = cbind(full_data, pred1, pred0)
## Prediction based on cross fitting
pred_a1_cf = predict(glm_fit_b1, newdata = full_data%/%filter(S=="a"), type = "response")
pred_a0_cf = predict(glm_fit_b0, newdata = full_data%/filter(S=="a"), type = "response")
pred_b1_cf = predict(glm_fit_a1, newdata = full_data%/filter(S=="b"), type = "response")
pred_b0_cf = predict(glm_fit_a0, newdata = full_data%/filter(S=="b"), type = "response")
pred1 = rep(NA, n)
pred0 = rep(NA, n)
pred1[S=="a"] = pred_a1_cf
pred0[S=="a"] = pred a0 cf
pred1[S=="b"] = pred_b1_cf
pred0[S=="b"] = pred_b0_cf
full_data_cf = cbind(full_data_cf, pred1, pred0)
# Linear calibration for the model
lm_fit_a1 = lm(Y~pred1+pred0, data = full_data %% filter(S == "a" & Z == 1))
lm_fit_a0 = lm(Y~pred1+pred0, data = full_data %% filter(S == "a" & Z == 0))
lm_fit_b1 = lm(Y~pred1+pred0, data = full_data %>% filter(S == "b" & Z == 1))
lm_fit_b0 = lm(Y~pred1+pred0, data = full_data %>% filter(S == "b" & Z == 0))
# Cross fit based on linear calibration
pred_a1_cf_lc = predict(lm_fit_b1, newdata = full_data_cf%/%filter(S == "a"))
pred_a0_cf_lc = predict(lm_fit_b0, newdata = full_data_cf%%filter(S == "a"))
pred_b1_cf_lc = predict(lm_fit_a1, newdata = full_data_cf%/%filter(S == "b"))
pred_b0_cf_lc = predict(lm_fit_a0, newdata = full_data_cf%%filter(S == "b"))
pred1_lc = rep(NA, n)
pred0_lc = rep(NA, n)
pred1_lc[S == "a"] = pred_a1_cf_lc
pred0_lc[S == "a"] = pred_a0_cf_lc
pred1_lc[S == "b"] = pred_b1_cf_lc
pred0_lc[S == "b"] = pred_b0_cf_lc
full_data_cf = cbind(full_data_cf, pred1_lc, pred0_lc)
## getting residuals
```

```
full_data_cf = full_data_cf %>%
   mutate(epsilon = case_when(
    Z == 1 \sim Y - pred1_lc,
    Z == 0 \sim Y - pred0 lc
   ))
 # Construct estimator
 ## point estimator
 mu_cf_a1 = 1/na * sum(full_data_cf$epsilon[S=="a" & Z==1])/(na1/na) + 1/na * sum(pred1_lc[S=="a"])
 mu_cf_a0 = 1/na * sum(full_data_cf$epsilon[S=="a" & Z==0])/(na0/na) + 1/na * sum(pred0_lc[S=="a"])
 mu_cf_b1 = 1/nb * sum(full_data_cf$epsilon[S=="b" & Z==1])/(nb1/nb) + 1/nb * sum(pred1_lc[S=="b"])
 mu_cf_b0 = 1/nb * sum(full_data_cf$epsilon[S=="b" & Z==0])/(nb0/nb) + 1/nb * sum(pred0_lc[S=="b"])
 tau_hat_cf = na/n * (mu_cf_a1-mu_cf_a0) + nb/n * (mu_cf_b1-mu_cf_b0)
   na^2/n^2 * (var(full_data_cf$epsilon[S=="a" & Z==1])/na1 + var(full_data_cf$epsilon[S=="a" & Z==0])
   nb^2/n^2 * (var(full_data_cf$epsilon[S=="b" & Z==1])/nb1 + var(full_data_cf$epsilon[S=="b" & Z==0])
 result_wrong_model[[split_index]]$tau[iter] = tau
 result_wrong_model[[split_index]]$tau_hat_0[iter] = tau_hat_0
 result_wrong_model[[split_index]] \squar_hat_0[iter] = var_hat_0
 result_wrong_model[[split_index]]$tau_hat_cf[iter] = tau_hat_cf
 result_wrong_model[[split_index]] $var_hat_cf[iter] = var_hat_cf
}
close(pb)
## [1] "split_index: 1"
## -----
## [1] "split_index: 2"
## ========
## [1] "split_index: 3"
## ========
## [1] "split_index: 4"
## [1] "split_index: 5"
## ========
## [1] "split index: 6"
## -----
## [1] "split index: 7"
```

#### Summarize results

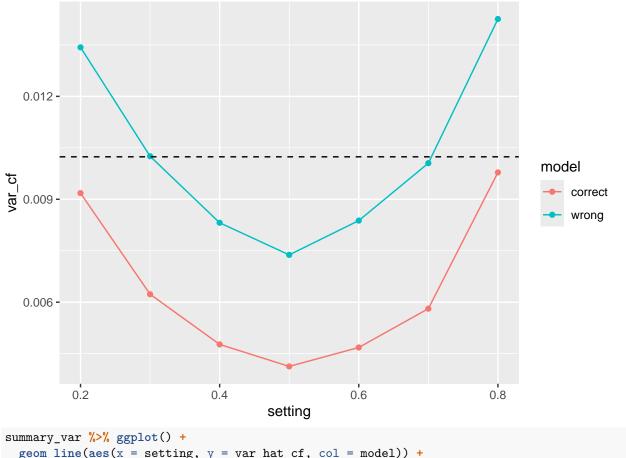
#### combined results

```
# combined data
combined_results_correct_model = do.call(rbind, lapply(1:length(split_setting), function(i) {
    # Add a "setting" column to each data frame
    result_correct_model[[i]]$setting = split_setting[i]
    return(result_correct_model[[i]])
}))
```

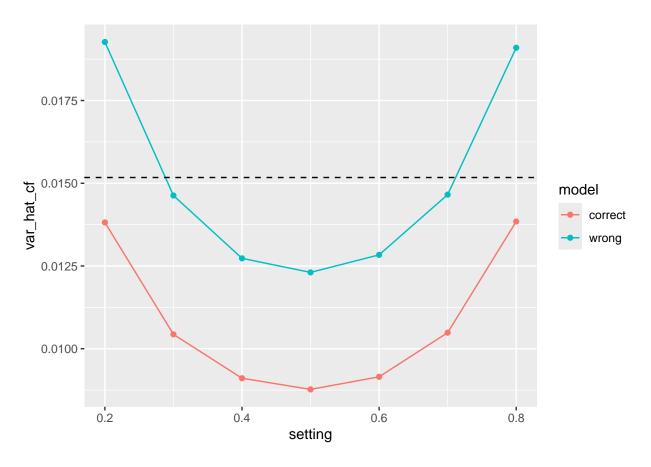
```
combined_results_wrong_model = do.call(rbind, lapply(1:length(split_setting), function(i) {
    # Add a "setting" column to each data frame
    result_wrong_model[[i]]$setting = split_setting[i]
    return(result_wrong_model[[i]])
}))
```

#### plot variance comparisons

```
# get mean variance without cross-fitting
var_0 = var(c(combined_results_correct_model$tau_hat_0,
              combined_results_wrong_model$tau_hat_0))
var_hat_0 = mean(c(combined_results_correct_model$var_hat_0,
                   combined_results_wrong_model$var_hat_0))
# get summary data for variance
summary var = rbind(
  combined_results_correct_model %>%
    group_by(setting) %>%
    summarize(
      var_cf = var(tau_hat_cf),
      var_hat_cf = mean(var_hat_cf)
    ) %>%
    mutate(model = "correct"),
  combined_results_wrong_model %>%
    group_by(setting) %>%
    summarize(
      var_cf = var(tau_hat_cf),
     var_hat_cf = mean(var_hat_cf)
    ) %>%
    mutate(model = "wrong")
)
# %>%
  pivot_longer(
#
#
     cols = c("var_cf", "var_hat_cf"),
#
     names_to = "var_type",
#
     values_to = "value"
#
summary_var %>% ggplot() +
  geom_line(aes(x = setting, y = var_cf, col = model)) +
  geom_point(aes(x = setting, y = var_cf, col = model)) +
  geom_hline(yintercept = var_0, lty = 2)
```

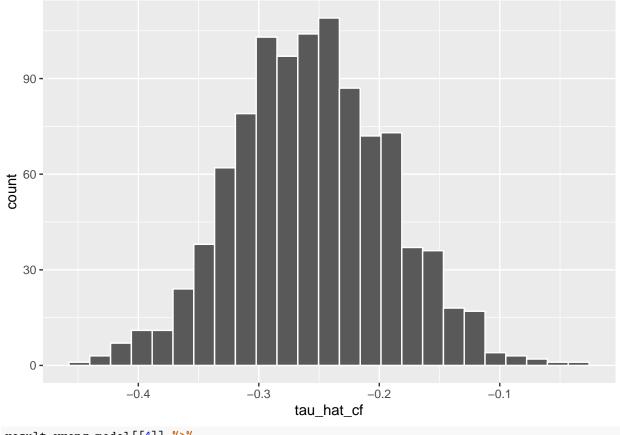


```
summary_var %>% ggplot() +
geom_line(aes(x = setting, y = var_hat_cf, col = model)) +
geom_point(aes(x = setting, y = var_hat_cf, col = model)) +
geom_hline(yintercept = var_hat_0, lty = 2)
```

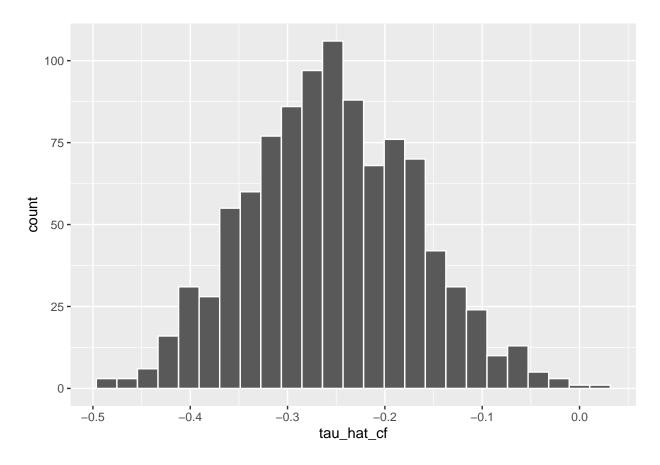


## Distribution check

```
# At the optimal variance case, the distribution is asymptotically normal
result_correct_model[[4]] %>%
    ggplot() +
    geom_histogram(aes(x = tau_hat_cf), col = "white", bins = 25)
```

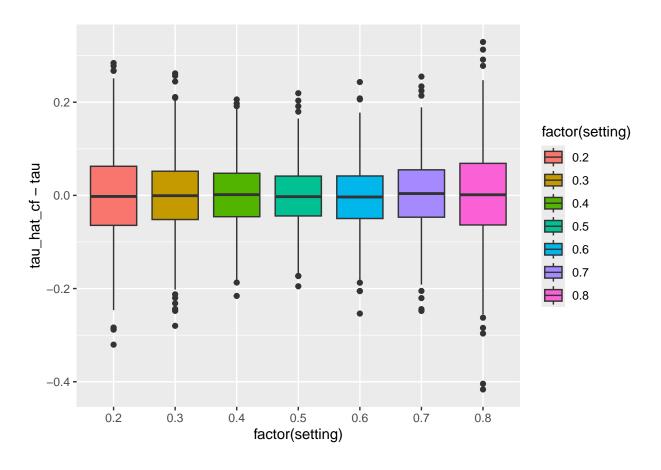


```
result_wrong_model[[4]] %>%
   ggplot() +
   geom_histogram(aes(x = tau_hat_cf), col = "white", bins = 25)
```



## bias check

```
combined_results_correct_model %>%
   ggplot() +
   geom_boxplot(aes(x=factor(setting), y=tau_hat_cf-tau, fill = factor(setting)))
```



Setting 2:

Setting 3: Comparison with the strategy of FZ under Bernoulli trial

Setting 4: SRE setting and Matched Pair setting