Part 3: Comparing causal model evaluations on the welfare question

Austin Murphy, Fred Lu

6/3/2020


```r
# Downloading script
# df <- readr::read_csv(file = "https://raw.githubusercontent.com/gsbDBI/ExperimentData/master/Welfare/ProcessedDat

# readr::write_csv(df, here::here("data/welfare.csv"))

# Read in provided welfare data
df <- readr::read_csv(file = here::here("data","welfare.csv"), na = character())
# Read in additional survey data
black_assistance <- readr::read_csv(file = here::here("data","black_assistance.csv"))
df <-
  df %>%
  dplyr::left_join(black_assistance)

# Specify outcome, treatment, and covariate variable names to use
outcome_variable_name <- "y" # or y_race for the other outcome variable
treatment_variable_name <- "w"
covariate_names <- c("partyid", "polviews", "age", "educ", "year", "attblack")

# Combine all names
all_variables_names <- c(outcome_variable_name, treatment_variable_name, covariate_names)
df <- df[, which(names(df) %in% all_variables_names)]

# Rename variables
names(df)[names(df) == outcome_variable_name] <- "Y"
names(df)[names(df) == treatment_variable_name] <- "W"

dim(df)
```

```
## [1] 36501     8
```

```r
colnames(df)
```

```
## [1] "year"     "age"      "educ"     "partyid"  "polviews" "W"        "Y"
## [8] "attblack"
```

```r
head(df)
```

```
## # A tibble: 6 x 8
##    year   age  educ partyid polviews     W     Y attblack
##   <int> <int> <int>   <int>    <dbl> <int> <int>    <dbl>
## 1  1986    28    14       3        4     0     0    0.333
## 2  1986    54    16       6        6     0     1    0.5
## 3  1986    44    16       0        2     0     1    0.75
## 4  1986    77    14       0        4     0     0    0.5
## 5  1986    44    14       0        4     0     0    0.5
## 6  1986    47    10       1        1     0     0    0.5
```

```r
# Filter out missing data
df <-
  df %>%
  filter_all(all_vars(. != -999)) %>%
  filter(partyid != 7)

# polviews has some values that are 4.1220088 for no reason... remove those
is.wholenumber <-
  function(x, tol = .Machine$double.eps^0.5)  abs(x - round(x)) < tol
df <- df[is.wholenumber(df$polviews),]
head(df)
```

```
## # A tibble: 6 x 8
##    year   age  educ partyid polviews     W     Y attblack
##   <int> <int> <int>   <int>    <dbl> <int> <int>    <dbl>
## 1  1986    28    14       3        4     0     0    0.333
## 2  1986    54    16       6        6     0     1    0.5
## 3  1986    44    16       0        2     0     1    0.75
## 4  1986    77    14       0        4     0     0    0.5
## 5  1986    44    14       0        4     0     0    0.5
## 6  1986    47    10       1        1     0     0    0.5
```

Recall that the ATE is -0.33 on this dataset. Earlier we used BART to estimate heterogeneous treatment effects. We now try some comparison methods. (Note that the negative sign is based on the convention of $W = 1$ being treatment. In our report and the original paper the opposite is more interpretable.)

```r
mean(df$Y[df$W == 1]) - mean(df$Y[df$W == 0])
```

```
## [1] -0.3333626
```

Models for estimating CATE

X-learner

Before fitting the X-learner, first generate, as simple comparisons, model fits with the S-learner and T-learner strategies. We would anticipate that the X-learner would give similar results to BART, both of which would be more effective than S or T learner.

```r
testidx <- base::sample(nrow(df), 5000)
df_train <- df[-testidx, ]
df_test <- df[testidx, ]

X <- df_train[,covariate_names]
W <- df_train$W
Y <- df_train$Y
num.trees <- 1000

# s learner
slearn <- regression_forest(df_train[,c(covariate_names,'W')], Y, num.trees=num.trees)

# t learner
n_train <- dim(df_train)[1]
tf0 <- regression_forest(X[W==0,], Y[W==0], num.trees=num.trees)
tf1 <- regression_forest(X[W==1,], Y[W==1], num.trees=num.trees)
```

Now estimate HTEs via the X-learner strategy, using regression forests for the nuisance components.

```r
# Compute the 'imputed treatment effects' using the other group
D1 <- Y[W==1] - predict(tf0, X[W==1,])$predictions
D0 <- predict(tf1, X[W==0,])$predictions - Y[W==0]

# Compute the cross estimators
xf0 <- regression_forest(X[W==0,], D0, num.trees=num.trees)
xf1 <- regression_forest(X[W==1,], D1, num.trees=num.trees)

# Predict treatment effects, making sure to always use OOB predictions where appropriate
xf.preds.0 <- rep(0, n_train)
xf.preds.0[W==0] <- predict(xf0)$predictions
xf.preds.0[W==1] <- predict(xf0, X[W==1,])$predictions
xf.preds.1 <- rep(0, n_train)
xf.preds.1[W==0] <- predict(xf0)$predictions
xf.preds.1[W==1] <- predict(xf0, X[W==1,])$predictions

# Estimate the propensity score
propf <- regression_forest(X, W, num.trees=num.trees)
ehat <- predict(propf)$predictions

# Finally, compute the X-learner prediction
tauhat_xl <- (1 - ehat) * xf.preds.1 + ehat * xf.preds.0
```

Causal Forest

Train a causal forest and compute (out-of-bag) CATE estimates on the training set.

```r
cf <- causal_forest(
  X = df_train[, covariate_names],
  Y = df_train$Y,
  W = df_train$W,
  num.trees=1000
)

oob_pred <- predict(cf, estimate.variance=TRUE)
```

BART model

Fit the BART model again, to enable test set comparisons with the other models

```r
test_w0 = df_test %>% select(-Y)
test_w1 = df_test %>% select(-Y)
test_w0$W = 0
test_w1$W = 1
x.test = as.data.frame(rbind(test_w0, test_w1))

bart = pbart(x.train = as.data.frame(df_train %>% select(-Y)),
             y.train = df_train$Y,
             x.test = x.test,
             nskip = 1000)
```

```
## *****Into main of pbart
## *****Data:
## data:n,p,np: 14738, 7, 10000
## y1,yn: 0, 0
## x1,x[n*p]: 1986.000000, 0.500000
## xp1,xp[np*p]: 2002.000000, 0.250000
## *****Number of Trees: 50
## *****Number of Cut Points: 14 ... 6
## *****burn and ndpost: 1000, 1000
## *****Prior:mybeta,alpha,tau: 2.000000,0.950000,0.212132
## *****binaryOffset: -0.626675
## *****Dirichlet:sparse,theta,omega,a,b,rho,augment: 0,0,1,0.5,1,7,0
## *****nkeeptrain,nkeeptest,nkeeptreedraws: 1000,1000,1000
## *****printevery: 100
## *****skiptr,skipte,skiptreedraws: 1,1,1
##
## MCMC
## done 0 (out of 2000)
## done 100 (out of 2000)
## done 200 (out of 2000)
## done 300 (out of 2000)
## done 400 (out of 2000)
## done 500 (out of 2000)
## done 600 (out of 2000)
## done 700 (out of 2000)
## done 800 (out of 2000)
## done 900 (out of 2000)
## done 1000 (out of 2000)
## done 1100 (out of 2000)
## done 1200 (out of 2000)
## done 1300 (out of 2000)
## done 1400 (out of 2000)
## done 1500 (out of 2000)
## done 1600 (out of 2000)
## done 1700 (out of 2000)
## done 1800 (out of 2000)
## done 1900 (out of 2000)
## time: 98s
## check counts
## trcnt,tecnt: 1000,1000
```

```r
# Process BART predictions to get in same format (treatment effect for each entry)
pred_w0 = bart$prob.test.mean[1:5000]
pred_w1 = bart$prob.test.mean[5001:10000]
tauhat_bart_test <- pred_w1 - pred_w0
```

```r
X_test <- df_test[,covariate_names]
tauhat_s_test <- predict(slearn, df_test[,c(covariate_names,'W')])

tauhat_t_test <- numeric(nrow(df_test))
tauhat_t_test[which(df_test$W==1)] <- predict(tf1, X_test[df_test$W==1, ])$predictions
tauhat_t_test[which(df_test$W==0)] <- predict(tf1, X_test[df_test$W==0, ])$predictions

X_test <- df_test[,covariate_names]
ehat.test <- predict(propf, X_test)$predictions
xf.preds.1.test <- predict(xf1, X_test)$predictions
xf.preds.0.test <- predict(xf0, X_test)$predictions
tauhat_xl_test <- (1 - ehat.test) * xf.preds.1.test + ehat.test * xf.preds.0.test

test_pred <- predict(cf, as.matrix(df_test[,covariate_names]), estimate.variance=TRUE)
tauhat_cf_test <- test_pred$predictions


# Compute Y-star
p <- mean(df_test$W)
Y_star <- ((df_test$W - p)/(p*(1-p)))*df_test$Y

# Compute the sample average treatment effect to use as a baseline comparison
tauhat_sample_ate <- with(df_train, mean(Y[W==1]) - mean(Y[W==0]))

# Compute test mse for all methods
mse <- data.frame(
  Sample_ATE_Loss = (Y_star - tauhat_sample_ate)^2,
  BART_Loss = (Y_star - tauhat_bart_test)^2,
  Causal_Forest_Loss = (Y_star - tauhat_cf_test)^2,
  X_Learner_Loss = (Y_star - tauhat_xl_test)^2,
  S_Learner_Loss = (Y_star - tauhat_s_test$predictions)^2,
  T_Learner_Loss = (Y_star - tauhat_t_test)^2)

print('Mean')
```

```
## [1] "Mean"
```

```r
colMeans(mse)
```

```
##    Sample_ATE_Loss          BART_Loss Causal_Forest_Loss     X_Learner_Loss
##          1.0007973          0.9887360          0.9909984          0.9903493
##     S_Learner_Loss     T_Learner_Loss
##          1.6265117          1.2076632
```

```r
print('SD')
```

```
## [1] "SD"
```

```r
apply(mse, 2, sd)
```

```
##    Sample_ATE_Loss          BART_Loss Causal_Forest_Loss     X_Learner_Loss
##           1.536451           1.547347           1.544625           1.545251
##     S_Learner_Loss     T_Learner_Loss
##           2.602909           1.956386
```

As expected, BART, causal forest, and X-learner outperform S learner and T learner. Note that BART, causal forest, and X-learner perform very similarly.

```r
Y.forest.test = regression_forest(X = as.matrix(df_test[covariate_names]), Y = df_test$Y)
Y.hat.test = predict(Y.forest.test)$predictions
W.forest.test = regression_forest(X = as.matrix(df_test[covariate_names]), Y = df_test$W)
W.hat.test = predict(W.forest.test)$predictions

mse_rloss <- data.frame(
  Sample_ATE_Loss = (df_test$Y - Y.hat.test - (df_test$W - W.hat.test) * tauhat_sample_ate)^2,
  BART_Loss = (df_test$Y - Y.hat.test - (df_test$W - W.hat.test) * tauhat_bart_test)^2,
  Causal_Forest_Loss = (df_test$Y - Y.hat.test - (df_test$W - W.hat.test) * tauhat_cf_test)^2,
  X_Learner_Loss = (df_test$Y - Y.hat.test - (df_test$W - W.hat.test) * tauhat_xl_test)^2,
  S_Learner_Loss = (df_test$Y - Y.hat.test - (df_test$W - W.hat.test) * tauhat_s_test$predictions)^2,
  T_Learner_Loss = (df_test$Y - Y.hat.test - (df_test$W - W.hat.test) * tauhat_xl_test)^2
)

print('Mean')
```

```
## [1] "Mean"
```

```r
colMeans(mse_rloss)
```

```
##    Sample_ATE_Loss          BART_Loss Causal_Forest_Loss     X_Learner_Loss
##          0.1611311          0.1588524          0.1591312          0.1589986
##     S_Learner_Loss     T_Learner_Loss
##          0.2652901          0.1589986
```

```r
print('SD')
```

```
## [1] "SD"
```

```r
apply(mse_rloss, 2, sd)
```

```
##    Sample_ATE_Loss          BART_Loss Causal_Forest_Loss     X_Learner_Loss
##          0.1873270          0.1973481          0.1947029          0.1955534
##     S_Learner_Loss     T_Learner_Loss
##          0.3441243          0.1955534
```

The same trend is observed using R-loss as the performance evaluation.