# python in R

## python environment setting

```
use_condaenv("final")
bartpy <- import("bartpy2.sklearnmodel")
#time_py <- import("time")
numpy <- import("numpy")

# unnormalize function from [-0.5,0.5]
unnormalize_x <- function(y_train,y_new){
    x <- data.frame()
    y_min <- min(y_train)
    y_max <- max(y_train)
    for (i in 1:nrow(y_new)) {
        for (j in 1:ncol(y_new)) {
            x[i,j] <- (y_max-y_min)*(y_new[i,j]+0.5)+y_min
        }
    }
    return(x)
}</pre>
```

### create dataset

```
linear_dgp_fun <- function(ratio,n, p, noise_sd) {
   set.seed(123)
   n_train <- n*ratio
   beta <- sample(1:100, p, replace = FALSE)

#n <- n_train + n_test
   X <- matrix(rnorm(n * p), nrow = n, ncol = p)</pre>
```

```
y <- X %*% beta + rnorm(n, sd = noise_sd)
  data_list <- list(</pre>
    X_train = X[1:n_train, , drop = FALSE],
    y_train = y[1:n_train],
    X_test = X[(n_train + 1):n, , drop = FALSE],
    y_{test} = y[(n_{train} + 1):n]
  return(data_list)
}
linear_dgp <- create_dgp(</pre>
  .dgp_fun = linear_dgp_fun, .name = "Linear DGP",
  # additional named parameters to pass to .dgp_fun()
  ratio = 0.8, n = 500, p = 4, noise_sd = 1
dataset_dgp_fun <- function(datasetname){</pre>
  address <- "C:/Users/pyk/Desktop/nus/RA/project/imodels-data-master/data_cleaned/"</pre>
  file <- paste0(datasetname,".csv")</pre>
  file_path <- paste0(address,file)</pre>
  df <- read.csv(file_path)</pre>
  x \leftarrow df[, -ncol(df)]
  y <- df[, ncol(df)]
  train_indices <- createDataPartition(y, p = 0.8, list = FALSE)</pre>
  data_list <- list(</pre>
    X_train <- x[train_indices, ],</pre>
    y_train <- y[train_indices],</pre>
    X_test <- x[-train_indices, ],</pre>
    y_test <- y[-train_indices]</pre>
  return(data_list)
}
dataset_dgp <- create_dgp(.dgp_fun = dataset_dgp_fun,.name = 'heart',</pre>
                             datasetname = "heart")
```

#### build BART model

```
BART_fun <- function(X_train, y_train, X_test, y_test, df,k,q,nchain,budget) {</pre>
  train_X <- data.frame(X_train)</pre>
  test_X <- data.frame(X_test)</pre>
  time \leftarrow 0
  posterior <- data.frame()</pre>
  for (i in 1:nchain) {
    t <- bench::mark(fit <- wbart(x.train = train X,
                                   y.train = y_train,
                                   x.test = test_X,
                                   k = k,
                                   sigdf = df,
                                   sigquant = q,
                                   ndpost = budget/nchain
                                   ))
    time <- time+mean(t$time[[1]])</pre>
    posterior <- rbind(posterior, fit$yhat.test)</pre>
  }
  #predictions <- colMeans(fit$yhat.test)</pre>
  predictions <- colMeans(posterior)</pre>
  mse_score <- mean((y_test - predictions)^2)</pre>
  lower_bounds <- apply(posterior, 2, quantile, probs = 0.025)</pre>
  upper_bounds <- apply(posterior, 2, quantile, probs = 0.975)
  coverage <- mean(y_test >= lower_bounds & y_test <= upper_bounds)</pre>
  return(list(time = time, mse=mse_score,coverage = coverage))
}
dbarts_fun <- function(X_train, y_train, X_test, y_test, df,k,q,nchain,budget){
  train_X <- data.frame(X_train)</pre>
  test_X <- data.frame(X_test)</pre>
  t <- bench::mark(bart_model <- dbarts::bart(x.train = train_X,
                                          y.train = y_train,
                                          x.test = test_X,
                                          k = k,
                                           sigdf = df,
                                           sigquant = q,
                                           nchain = nchain,
                                           ndpost = budget))
  time <- mean(t$time[[1]])</pre>
```

```
predictions <- colMeans(bart_model$yhat.test)</pre>
  mse_score <- mean((y_test - predictions)^2)</pre>
  lower_bounds <- apply(bart_model$yhat.test, 2, quantile, probs = 0.025)</pre>
  upper_bounds <- apply(bart_model$yhat.test, 2, quantile, probs = 0.975)
  coverage <- mean(y_test >= lower_bounds & y_test <= upper_bounds)</pre>
  return(list(time = time, mse=mse_score,coverage = coverage))
bartMachine_fun <- function(X_train, y_train, X_test,y_test,df,k,q,nchain,budget){</pre>
  train_X <- data.frame(X_train)</pre>
  test_X <- data.frame(X_test)</pre>
  posterior <- data.frame()</pre>
  time <-0
  CI <- matrix(0, nrow = nrow(test_X), ncol = 2)</pre>
  ndpost <- budget/nchain</pre>
  t <- bench::mark(bart_model <- bartMachine(</pre>
        X = train_X,
        y = y_train,
        k = k
        nu = df,
        q=q,
        num_burn_in = 100,
        num_iterations_after_burn_in = ndpost))
        # The value of calculating the time required for modeling
  time <- time+mean(t$time[[1]])</pre>
  posterior <- rbind(posterior,predict(bart_model,test_X,type = "prob"))</pre>
  CI <- CI+calc_credible_intervals(bart_model,test_X)</pre>
  predictions <- colMeans(posterior)</pre>
  #predictions <- predict(bart_model,test_X,type = "prob")</pre>
  mse_score <- mean((y_test - predictions)^2)</pre>
  #CI <- calc_credible_intervals(bart_model,test_X)</pre>
  coverage <- mean(y_test >= CI[,1]/nchain & y_test <= CI[,2]/nchain)</pre>
  return(list(time = time, mse=mse_score,coverage = coverage))
}
```

```
SoftBart_fun<- function(X_train, y_train, X_test,y_test,num_trees,alpha,beta){
  train_X <- data.frame(X_train)</pre>
  test X <- data.frame(X test)</pre>
  t <- bench::mark({bart_model <- softbart(X = train_X, Y = y_train, X_test = test_X, hypers
  time <- mean(t$time[[1]])
  predictions <- bart_model$y_hat_test_mean</pre>
  mse_score <- mean((y_test - predictions)^2)</pre>
  lower_bounds <- apply(bart_model$y_hat_test, 2, quantile, probs = 0.025)</pre>
  upper_bounds <- apply(bart_model$y_hat_test, 2, quantile, probs = 0.975)</pre>
  coverage <- mean(y_test >= lower_bounds & y_test <= upper_bounds)</pre>
  return(list(time = time, mse=mse_score,coverage = coverage))
}
RF_fun <- function(X_train, y_train, X_test,y_test){</pre>
  train_X <- data.frame(X_train)</pre>
  test_X <- data.frame(X_test)</pre>
  t <- bench::mark({rf_model <- randomForest(x=train_X, y=y_train)})
  time <- mean(t$time[[1]])</pre>
  predictions <- predict(rf_model, test_X)</pre>
  mse_score <- mean((y_test - predictions)^2)</pre>
 return(list(time = time, mse=mse_score))
}
bartpy_fun <- function(X_train, y_train, X_test,y_test){</pre>
  train_x <- numpy$array(X_train)</pre>
  train_y <- numpy$array(y_train)</pre>
  test_x <- numpy$array(X_test)</pre>
  test_y <- numpy$array(y_test)</pre>
  bart_model <- bartpy$SklearnModel(n_jobs=1)</pre>
  #start_time <- time_py$time()</pre>
  t <- bench::mark({yk <- bart_model$fit(train_x,train_y)})</pre>
  #time <- time_py$time-start_time</pre>
  time <- mean(t$time[[1]])</pre>
  predictions <- yk$predict(test_x)</pre>
  mse_score <- mean((test_y - predictions)^2)</pre>
```

```
## calculate coverage
  extract <- yk$extract</pre>
  model_samples <- extract[[1]][[1]]</pre>
  a <- data.frame()</pre>
  for (model in model_samples) {
    a <- rbind(a,model$predict(test_x))</pre>
  a_new <- unnormalize_x(train_y,a)</pre>
  lower_bounds <- apply(a_new, 2, quantile, probs = 0.025)</pre>
  upper_bounds <- apply(a_new, 2, quantile, probs = 0.975)
  coverage <- mean(test_y >= lower_bounds & test_y <= upper_bounds)</pre>
 return(list(time = time, mse=mse_score,coverage = coverage))
stochtree_fun <- function(X_train, y_train, X_test, y_test, q,nchain,budget){</pre>
  train_X <- data.frame(X_train)</pre>
  test_X <- data.frame(X_test)</pre>
  posterior <- matrix(0, nrow = nrow(test_X), ncol = 1)</pre>
  time <-0
  for (i in 1:nchain) {
    t <- bench::mark(bart_model <- stochtree::bart(X_train = train_X,
                                           y_train = y_train,
                                          X_test = test_X,
                                           q = q,
                                           num_burnin = 100))
    time <- time+mean(t$time[[1]])</pre>
    posterior <- cbind(posterior,bart_model$y_hat_test)</pre>
  posterior <- posterior[,-1]</pre>
  predictions <- rowMeans(posterior)</pre>
  mse_score <- mean((y_test - predictions)^2)</pre>
  lower_bounds <- apply(posterior, 1, quantile, probs = 0.025)</pre>
  upper_bounds <- apply(posterior, 1, quantile, probs = 0.975)</pre>
  coverage <- mean(y_test >= lower_bounds & y_test <= upper_bounds)</pre>
  return(list(time = time, mse=mse_score,coverage = coverage))
```

```
xgb_fun <- function(X_train, y_train, X_test,y_test){
   train_X <- data.frame(X_train)
   test_X <- data.frame(X_test)
   t <- bench::mark({xgb_model <- xgboost(data=as.matrix(train_X), label =y_train,nrounds = 1000 time <- mean(t$time[[1]])
   predictions <- predict(xgb_model, as.matrix(test_X))
   mse_score <- mean((y_test - predictions)^2)
   return(list(time = time, mse=mse_score))
}
</pre>
```

#### create evaluation

```
plot_mse <- function(fit_results){</pre>
  fit_results$time_numeric <- as.numeric(fit_results$time)</pre>
# Calculate MSE for each group
  summary <- fit_results %>%
    group_by(fit_results$.dgp_name, fit_results$.method_name,n,p,noise_sd,nchain) %>%
    summarise(
      Mean_MSE = mean(mse),
      Var_MSE = sd(mse),
      .groups = 'keep')
  plt <- ggplot(summary, aes(x = `fit_results$.method_name`, y = Mean_MSE</pre>
                     #fill = Category
                     )) +
    geom_bar(stat = "identity") +
    facet_grid(~n+p+noise_sd+nchain)+
    theme minimal() +
    theme(axis.text.x = element_text(angle = 45, hjust = 1))+
    labs(y = "MSE", x = "method")
    facet_wrap(~ `fit_results$.dgp_name`)
  return(plt)
  }
plot_time <- function(fit_results){</pre>
  fit_results$time_numeric <- as.numeric(fit_results$time)</pre>
```

```
# Calculate MSE for each group
  summary <- fit_results %>%
    group_by(fit_results$.dgp_name, fit_results$.method_name,n,p,noise_sd,nchain) %>%
    summarise(
      Mean_time = mean(time_numeric),
      Var_time = sd(time_numeric),
  plt <- ggplot(summary, aes(x = `fit_results$.method_name`, y = Mean_time</pre>
                    #fill = Category
                    )) +
    geom_bar(stat = "identity") +
    facet_wrap(~n+p+noise_sd+nchain) +
    theme_minimal() +
    theme(axis.text.x = element_text(angle = 45, hjust = 1))+
    labs(y = "time", x = "method")
   facet_wrap(~ `fit_results$.dgp_name`)
  return(plt)
  }
plot_coverage <- function(fit_results){</pre>
  fit_results$time_numeric <- as.numeric(fit_results$time)</pre>
# Calculate MSE for each group
    summary <- fit_results %>%
    group_by(fit_results$.dgp_name, fit_results$.method_name,n,p,noise_sd,nchain) %>%
    summarise(
      Mean_coverage=mean(coverage),
      SD_coverage = sd(coverage))
  plt <- ggplot(summary, aes(x = `fit_results$.method_name`, y = Mean_coverage)) +</pre>
    geom_bar(stat = "identity") +
    facet_grid(~n+p+noise_sd+nchain)+
    theme_minimal() +
    theme(axis.text.x = element_text(angle = 45, hjust = 1))+
    labs(y = "coverage", x = "method")
    facet_wrap(~ `fit_results$.dgp_name`)
  return(plt)
```

```
coverage_plot <- create_visualizer(
   .viz_fun = plot_coverage, .name = 'coverage Plot',
   # additional named parameters to pass to .viz_fun()

)

time_plot <- create_visualizer(
   .viz_fun = plot_time, .name = 'time Plot',
   # additional named parameters to pass to .viz_fun()

)

mse_plot <- create_visualizer(
   .viz_fun = plot_mse, .name = 'MSE Plot',
   # additional named parameters to pass to .viz_fun()

)</pre>
```

## model fitting

```
BART <- create_method(</pre>
  .method_fun = BART_fun, .name = "BART",
  k=2.5, q=0.95, df=4, nchain = 1, budget=1200
dbarts <- create_method(.method_fun = dbarts_fun,.name = "dbarts",</pre>
                         k=2.5, q=0.95, df=4, nchain = 1, budget=1200)
bartMachine <- create_method(.method_fun = bartMachine_fun,.name = "bartMachine",</pre>
                         k=2.5,q=0.95,df=4,budget=1200)
SoftBart <- create_method(.method_fun = SoftBart_fun,.name = "SoftBart",</pre>
                         num_trees=50,alpha=0.95,beta=2)
RF <- create method(.method fun = RF fun,.name = "RandomForest")
bartpy2 <- create_method(.method_fun = bartpy_fun,.name = "bartpy")</pre>
stochtree <- create_method(.method_fun = stochtree fun, .name = "stochtree",q=0.95,budget=12
XGB <- create_method(.method_fun = xgb_fun, .name = "XGBoost")</pre>
# Create experiment
experiment <- create_experiment(name = "Test Experiment") %>%
  add_dgp(linear_dgp) %>%
  #add_dgp(dataset_dgp) %>%
  add method(dbarts) %>%
  add_method(BART) %>%
  add_method(bartMachine) %>%
```

```
add_method(SoftBart) %>%
  add_method(RF)%>%
  add_method(bartpy2)%>%
  add_method(stochtree)%>%
  add method(XGB)%>%
  add_visualizer(mse_plot)%>%
  add_visualizer(time_plot)%>%
  add_visualizer(coverage_plot)%>%
  add_vary_across(
    .dgp = "Linear DGP",
   noise_sd = c(0.5),
   n=c(200),
   p=c(4,6)
  ) %>%
  add_vary_across(
    .method = c("BART", "dbarts", "bartMachine", "stochtree"),
   nchain=c(1,3)
  #add_evaluator(pred_err)
results <- run_experiment(experiment, n_reps = 2, save = TRUE)
Fitting Test Experiment...
Saving fit results...
Fit results saved | time taken: 0.030724 seconds
2 reps completed (totals: 2/2) | time taken: 4.029714 minutes
_____
No evaluators to evaluate. Skipping evaluation.
Visualizing Test Experiment...
`summarise()` has grouped output by 'fit_results$.dgp_name', 'fit_results$.method_name', 'n'
`summarise()` has grouped output by 'fit_results$.dgp_name', 'fit_results$.method_name', 'n'
Visualization completed | time taken: 0.002533 minutes
Saving viz results...
Viz results saved | time taken: 0.104996 seconds
______
# Render automated documentation and view results
#render_docs(experiment)
```

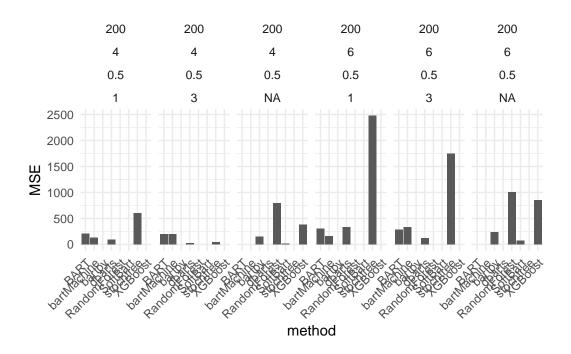
```
result <- results$fit_results
result$time_numeric <- as.numeric(result$time)
result</pre>
```

```
# A tibble: 48 x 11
  .rep .dgp_name .method_name noise_sd
                                                  p nchain time
                                           n
                                                                        {\tt mse}
                   <chr>
                                  <dbl> <dbl> <dbl> <dbl> <
  <chr> <chr>
                                                                      <dbl>
1 1
       Linear DGP BART
                                    0.5
                                          200
                                                         1 <bench_tm>
                                                                      214.
2 1
        Linear DGP BART
                                                         3 <bench_tm>
                                    0.5
                                          200
                                                  4
                                                                      198.
3 1
       Linear DGP BART
                                    0.5
                                          200
                                                         1 <bench_tm>
                                                                      300.
                                                  6
4 1
       Linear DGP BART
                                          200
                                                         3 <bench_tm>
                                    0.5
                                                  6
                                                                      288.
5 1
       Linear DGP RandomForest
                                    0.5
                                          200
                                                  4
                                                        NA <bench_tm>
                                                                      822.
6 1
       Linear DGP RandomForest
                                    0.5
                                          200
                                                  6
                                                        NA <bench_tm> 1009.
7 1
       Linear DGP SoftBart
                                    0.5
                                          200
                                                  4
                                                        NA <bench_tm>
                                                                       19.3
8 1
       Linear DGP SoftBart
                                    0.5
                                          200
                                                        NA <bench_tm>
                                                                       72.9
9 1
        Linear DGP XGBoost
                                    0.5
                                          200
                                                  4
                                                        NA <bench_tm>
                                                                      381.
10 1
       Linear DGP XGBoost
                                    0.5
                                          200
                                                  6
                                                        NA <bench_tm>
                                                                      847.
# i 38 more rows
```

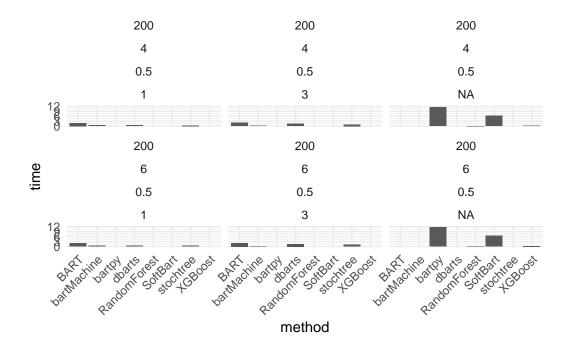
# i 2 more variables: coverage <dbl>, time\_numeric <dbl>

#### results\$viz\_results

\$`MSE Plot`

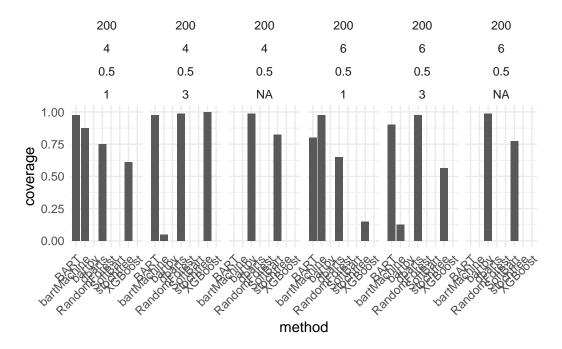


## \$`time Plot`



## \$`coverage Plot`

Warning: Removed 4 rows containing missing values or values outside the scale range (`geom\_bar()`).



"