The purpose of this document is to describe how to use the “qlearning” package in R using a simulated (fake) data set.

Q-Learning is used to construct a proposal for an optimal adaptive treatment strategy (also known as a dynamic treatment regime). An adaptive treatment strategy is a sequence of decision rules, one per critical decision point, that specifies whether, how, or when to alter the intensity, type, or delivery of treatment at critical decision points. The simulated (fake) data set used below mimics data arising from a sequential multiple assignment randomized trial (SMART) designed to inform how to treat children with ADHD using a sequence of treatments involving medication or behavioral modification. In the trial, children are initially randomized to either behavioral modification or medication. Non-responders to initial treatment are re-randomized to either intensify initial treatment or add the other treatment. Responders to initial treatment remain on their initially assigned treatment. For more information about adaptive treatment strategies and SMARTs please read:

I. Nahum-Shani, M. Qian, D. Almirall, W.. Pelham, B. Gnagy, G. Fabiano, J. Waxmonsky, J. Yu and S.A. Murphy (2010). Experimental Design and Primary Data Analysis Methods for Comparing Adaptive Interventions. Technical Report.

For more information about Q-Learning, please read:

I. Nahum-Shani, M. Qian, D. Almirall, W.. Pelham, B. Gnagy, G. Fabiano, J. Waxmonsky, J. Yu and S.A. Murphy (2010). Q-Learning: A Data Analysis Method for Constructing Adaptive Interventions. Technical Report.

```
## Since the confidence intervals are obtained using a bootstrap method, we use the
##“set.seed” comment to reproduce the same intervals.
 set.seed(14)
## load qlearning package
   library(qlearning)

## check the usage of the qlearning package
## this will help you understand the arguments to the function
   ?qlearning
##  (An html help page about the qlearning package will pop up.)

## load the example data set provided in the qlearning package
   data("DataEx")

## check the description of the example data set.
   ?DataEx
## (An html help page about the example data set will pop up.)

## take a look at the first few observations in the data
 head(DataEx)

## some data manipulation: center continues covariates, define others, etc.
## centering continues covariates makes it easier to contrast the effects of
## treatment

DataEx$ReRand <- 1 - DataEx$R ## R = 1 = responders are not ReRandomized
DataEx$O12c <- scale(DataEx$O12, center = TRUE, scale = FALSE)
DataEx$O21c <- scale(DataEx$O21, center = TRUE, scale = FALSE)
```

```
## we are going to use the qlearning() function to fit the following two models:
## stage 1 model: E(Y | A1, O11, O12, O13 ) = b1*H10 + b2*A1*H11
## stage 2 model: E(Y | A1, O11, O12, O13, A2, O11, O12 ) = b3*H20 + b4*A2*H21
## note:
## b1, b2, b3 and b4 are vectors.
## qlearning() assumes A1 and A2 are binary (-1/1).


## construct design matrices to be used in the first-stage and the second-stage
## regression
 H10 <- cbind(1, DataEx$O11, DataEx$O12c, DataEx$O13)
 H11 <- cbind(1, DataEx$O13)
 H20 <- cbind(1, DataEx$O11, DataEx$O12c, DataEx$O13, DataEx$A1, DataEx$O21c,
 DataEx$O22)
 H21 <- cbind(1, DataEx$A1, DataEx$O22)

## note: The stage 1 model has 6 parameters (the number of covariates in H10 plus
## the interaction ). The stage 2 model has 10 parameters (the number of covariates
## in H20 plus the interaction )


## Run qlearning function to get the regression coefficients and the associated
## confidence intervals
   object1 <- qlearning(
      H10=H10,
      H11=H11,
      A1=DataEx$A1,
      ReRand=DataEx$ReRand,
      H20=H20,
      H21=H21,
      A2=DataEx$A2,
      Y=DataEx$Y
)

## check the output
   object1
Call:
qlearning(H10 = H10, H11 = H11, A1 = DataEx$A1, ReRand = DataEx$ReRand,
    H20 = H20, H21 = H21, A2 = DataEx$A2, Y = DataEx$Y)

First-stage coefficients:
       H10.1        H10.2        H10.3        H10.4     H11.1:A1
  3.839640989 -0.151106514 -0.007272137 -0.204500175  0.249399868
    H11.2:A1
-0.465675897
Degrees of freedom for the first-stage regression: 144

Estimators and the 95 % confidence intervals for the first-stage contrasts
        Estimator       Lower      Upper
[1,]  3.839640989  3.49900447  4.0947560
[2,] -0.151106514 -0.55271742  0.2726967
[3,] -0.007272137 -0.18794098  0.1763734
[4,] -0.204500175 -0.64892585  0.2201592
[5,]  0.249399868  0.02640238  0.5118753
[6,] -0.465675897 -0.99212814 -0.1476497
```

```
Second-stage coefficients:
       H20.1        H20.2        H20.3        H20.4        H20.5
  3.360680169  0.156568810  0.001407086 -0.546072673  0.078264465
       H20.6        H20.7     H21.1:A2     H21.2:A2     H21.3:A2
-0.123935014  0.265568679 -0.728424621  0.054463251  1.306516945
Degrees of freedom for the second-stage regression: 79

Estimators and the 95 % confidence intervals for the second-stage contrasts
         Estimator      Lower       Upper
 [1,]  3.360680169  3.0210513  3.65315285
 [2,]  0.156568810 -0.3469857  0.69362783
 [3,]  0.001407086 -0.2256815  0.22685624
 [4,] -0.546072673 -1.1247980  0.05802638
 [5,]  0.078264465 -0.1872550  0.35552231
 [6,] -0.123935014 -0.2255430 -0.03262726
 [7,]  0.265568679 -0.1626656  0.72060687
 [8,] -0.728424621 -1.0508543 -0.42743282
 [9,]  0.054463251 -0.1590232  0.31951779
[10,]  1.306516945  0.8472303  1.76240351

## Extract the first-stage regression coefficients, degrees of freedom and the
##confidence interval for each coefficient from “object1”
   stage1coef(object1)
      H10.1        H10.2        H10.3        H10.4     H11.1:A1     H11.2:A1
 3.839640989 -0.151106514 -0.007272137 -0.204500175  0.249399868 -0.465675897

## if you want to know the stage 1 regression degrees of freedom, use this:
   stage1df(object1)
[1] 144

## if you want to extract just the coefficients, use this:
   stage1CI(object1)
       Estimator        Lower      Upper
[1,]  3.839640989  3.49900447  4.0947560
[2,] -0.151106514 -0.55271742  0.2726967
[3,] -0.007272137 -0.18794098  0.1763734
[4,] -0.204500175 -0.64892585  0.2201592
[5,]  0.249399868  0.02640238  0.5118753
[6,] -0.465675897 -0.99212814 -0.1476497


## Can do the same thing for the second-stage regression.

## you can use contrast statements with qlearning() to understand the effects
## of treatment for different subgroups of participants given their values of
## O1=(O11,O12,O13) and O2=(O21,O22). Here we show you an example:

## A1 = -1 = Medication
## A1 = 1  = Behavioral modification
## an example of a stage 1 contrast matrix
 C1 <- rbind(     c(1, 0, 0, 1, -1, -1),
                  c(1, 0, 0, 1,  1,  1),
                  c(0, 0, 0, 0, -2, -2)
             )
```

```
##The number of columns of C1 should be equal to number of parameters in the stage
##1 regression. The number of rows in C1 corresponds to the number of contrasts the
##user wishes to estimate.
##The first row of the C1 estimates (1,0,0,1)*b1 + (-1,-1)*b2 which is the mean
##response, Y, among participants with  O11=0, O12c=0, O13=1, A1=-1, A1*O13=-1
##plus the intercept.
##The second row of the C1 estimates (1,0,0,1)*b1 + (1,1)*b2 which is the mean
##response, Y, among participants with  O11=0, O12c=0, O13=1, A1=1, A1*O13=1 plus
##the intercept.
##The third row of the C1 estimates [(1,0,0,1)*b1 + (-1,-1)*b2]-[(1,0,0,1)*b1+
##(1,1)*b2]= (0,0,0,0)*b1 + (-2,-2)*b2 which is the mean response difference
##between participants with A1=-1 and A1=1 when O13=1.


## A2 = 1 = INTENSIFY initial txt
## A2 = -1 = ADD TO initial txt

 C2 <- rbind(     c(1, 0, 0, 0, -1, 0, 1,  1, -1,  1),
                  c(1, 0, 0, 0, -1, 0, 1, -1,  1, -1),
                  c(0, 0, 0, 0,  0, 0, 0,  2, -2,  2)
             )


##The number of columns of C2 should be equal to number of parameters in the stage
##2 regression. The number of rows in C2 corresponds to the number of contrasts the
##user wishes to estimate.
##The first row of the C2 estimates (1,0,0,0,-1,0,1)*b3 + (1,-1,1)*b4 which is
##the mean response, Y, among participants with  O11=0, O12c=0, O13=0, A1=-1,
##O21c=0, O22=1, A2=1, A1A2=-1, A2O22=1 plus the intercept.
##The second row of the C2 estimates (1,0,0,0,-1,0,1)*b3 + (-1,1,-1)*b4 which is
##the mean response, Y, among participants with  O11=0, O12c=0, O13=0, A1=-1,
##O21c=0, O22=1, A2=-1, A1A2=1, A2O22=-1 plus the intercept.
##The third row of the C2 estimates [1,0,0,0,-1,0,1)*b3 + (1,-1,1)*b4]-
##[(1,0,0,0,-1,0,1)*b3 + (-1,1,-1)*b4] which is the mean response difference
##between A2=1 and A2=-1 when A1=-1 and O22=1.

## Run qlearning function to get estimates and confidence intervals for the
##contrasts
   object2 <- qlearning(
      H10=H10,
      H11=H11,
      A1=DataEx$A1,
      ReRand=DataEx$ReRand,
      H20=H20,
      H21=H21,
      A2=DataEx$A2,
      Y=DataEx$Y,
      C1=C1,
      C2=C2
)

   stage1CI(object2)
      Estimator       Lower      Upper
[1,] 3.8514168  3.2532030 4.415197
[2,] 3.4188648  2.8811401 3.840728
[3,] 0.4325521 -0.2162382 1.273855
```

```
##Comparing the first two contrast estimates, we conclude that among kids who have
##found medication acceptable in the past (O13=1) and O11=0, O12c=0, being treated
##initially with medication results in a mean outcome of 3.85, whereas being
##treated initially with behavioral modification results in a mean outcome of
##3.42.  Therefore, as shown in the third contrast, among kids who have found
##medication acceptable in the past (O13=1) and O11=0, O12c=0, being treated
##initially with medication results in a higher response than behavioral
##modification.

##Using similar contrast statements, the reader can verify that among participants
##with O13=0, being treated initially with behavioral modification treatment is
##better than being treated initially with medication. Therefore, this suggests
##that medication acceptability (O13) can be used to tailor first-stage treatment.
```

```
   stage2CI(object2)
      Estimator      Lower     Upper
[1,]  4.071613 3.4319386 4.697679
[2,]  3.024355 2.4490052 3.593617
[3,]  1.047258 0.1973167 1.878840
```

```
##Comparing the first two contrast estimates, we conclude that among kids who have
##O13=0 and O11=0, O12c=0, A1=-1, O21c=0, O22=1, intensifying the initial
##treatment results in a mean outcome of 4.07, whereas augmenting the initial
##treatment results in a mean outcome of 3.02.  Therefore, as shown in the third
##contrast, among kids who have O13=0 and O11=0, O12c=0, A1=-1, O21c=0, O22=1,
##intensifying the initial treatment  results in a higher response than augmenting
##it with another treatment.

##Using similar contrast statements, the reader can verify that among participants
##with O22=0, augmenting initial treatment is better than intensifying initial
##treatment. Therefore, this suggests that adherence to first-line treatment (O22)
##can be used to tailor second-stage treatment.
```