ATEHonest: Honest CIs for Average Treatment Effects

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The package `ATEHonest` implements honest confidence intervals and estimators for estimating average treatment effects under unconfoundedness from Armstrong and Kolesár [2018]. Here we illustrate the use of the package using NSW data from Dehejia and Wahba [1999].

The data is shipped with the package, as two data frames, `NSW` (where the treated units are from the experimental sample and control units are from PSID), and `NSWexper`, where both treated and control units are from the experimental sample. We'll use the experimental sample here.

First we extract the design matrix, and the treatment and outcome vectors, and we construct a nearest neighbor estimate of the variance of the regression errors using Mahalanobis distance:

```r
library("ATEHonest")
X <- as.matrix(NSWexper[, 2:10])
d <- NSWexper$treated
y <- NSWexper$re78
DMvar <- distMat(X, chol(solve(cov(X))), method = "euclidean")
sigma2 <- nnvar(DMvar, d, y, J = 3)
```

Next, we compute matrix of distances between treated and control units, using the same weight matrix to compute distances as in Armstrong and Kolesár [2018]:

```r
Ahalf <- diag(c(0.15, 0.6, 2.5, 2.5, 2.5, 0.5, 0.5, 0.1,
    0.1))
D0 <- distMat(X, Ahalf, method = "manhattan", d)
```

We now compute the first few steps of the solution path. 150 steps will be sufficient for computing the optimal estimator. Given the solution path, we then compute the root mean squared error optimal estimator, as well as estimator that's optimal for constructing two-sided CIs:

```r
res <- ATTh(D0, maxiter = 150)$res
op <- ATTOptPath(res, y, d)
ATTOptEstimate(op, mean(sigma2), C = 1, sigma2final = sigma2,
    opt.criterion = "RMSE")
#>
#>
#> Estimate    Max. bias    SE          CI                        delta
#> ---------   ----------   ----------  ----------------------    ---------
#> 1.58946     1.185779     0.7550322   (-0.8382422, 4.017163)    1.222493
ATTOptEstimate(op, mean(sigma2), C = 1, sigma2final = sigma2,
```

1

```
      opt.criterion = "FLCI")
#>
#>
#> Estimate    Max. bias    SE          CI                          delta
#> ---------   ----------   ---------   ----------------------   ---------
#> 1.62276     1.234971     0.713424    (-0.7856902,  4.03121)    3.289782
```

Efficiency of one- and two-sided CIs at smooth functions (see Appendix A in Armstrong and Kolesár [2018]) is:

```
ATTEffBounds(res, d, mean(sigma2), C = 1)
#> Warning in ATTEffBounds(res, d, mean(sigma2), C = 1): Path too short to compute
#> two-sided efficiency
#> $onesided
#> [1] 0.9917693
#>
#> $twosided
#> [1] NaN
```

For comparison, we also consider matching estimators. First, a matching estimator with a single match:

```
ATTMatchEstimate(ATTMatchPath(y, d, D0, M = 1, tol = 1e-12),
    mean(sigma2), C = 1, sigma2final = sigma2)
#>
#>
#> Estimate    Max. bias    SE          CI                          M
#> ---------   ----------   ----------  ----------------------   ---
#> 1.972065    1.169562     0.7758019   (-0.4735895,  4.41772)     1
```

Next, we optimize the number of matches. For that we first compute the matching estimator for a vector of matches M, and then optimize the number of matches using ATTMatchEstmate:

```
mp <- ATTMatchPath(y, d, D0, M = 1:10, tol = 1e-12)
ATTMatchEstimate(mp, mean(sigma2), C = 1, sigma2final = sigma2,
    opt.criterion = "FLCI")
#>
#>
#> Estimate    Max. bias    SE          CI                          M
#> ---------   ----------   ----------  ----------------------   ---
#> 1.972065    1.169562     0.7758019   (-0.4735895,  4.41772)     1
ATTMatchEstimate(mp, mean(sigma2), C = 1, sigma2final = sigma2,
    opt.criterion = "RMSE")
#>
#>
#> Estimate    Max. bias    SE          CI                          M
#> ---------   ----------   ----------  ----------------------   ---
#> 1.972065    1.169562     0.7758019   (-0.4735895,  4.41772)     1
```

We can see that a single match is in fact optimal for both estimation and construction of two-sided

CIs.

References

Tim Armstrong and Michal Kolesár. Finite-sample optimal estimation and inference on average treatment effects under unconfoundedness. arXiv:1712.04594, December 2018.

Rajeev H. Dehejia and Sadek Wahba. Causal effects in nonexperimental studies: Reevaluating the evaluation of training programs. *Journal of the American Statistical Association*, 94(448):1053–1062, 1999.