Bias

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Structure of Class

- Today we're going to talk about:
  1. *apply functions
  2. Marginal Effects
  3. Sensitivity analysis for post-treament bias

The *apply family

- These functions allow one to *efficiently* perform a large number of actions on data.
- `apply` - performs actions on the rows or columns of a matrix/array (1 for rows, 2 for columns, 3 for ??)
- `sapply` - performs actions on every element of a vector
- `tapply` - performs actions on a vector by group
- `replicate` - performs the same action a given number of times

apply

```
A
```

```
##   c d
## a 1 3
## b 2 4
```

```
apply(A, 1, sum)
```

```
## a b
## 4 6
```

```
apply(A, 2, mean)
```

```
##   c   d
## 1.5 3.5
```

sapply

```
vec
```

```
## [1] "a" "b" "c"
```

```
sapply(vec, function(x) paste0(x, ".vec"))
```

```
##       a       b       c
## "a.vec" "b.vec" "c.vec"
```

- Can be accomplished more simply with:

. . .

```
paste0(vec, ".vec")
```

```
## [1] "a.vec" "b.vec" "c.vec"
```

- Why?
- `replicate` is basically just `sapply(1:N,funct)` where `funct` never uses the index.

tapply

```
tapply(1:10, makeGroups(5, 2), mean)
```

```
##   1   2   3   4   5
## 1.5 3.5 5.5 7.5 9.5
```

Local Linear Regression

- W is an $n \times p$ diagonal weighting matrix, h is a "bandwidth".
- Diagonal entries are $\frac{3}{4} \cdot (1 - d^2) \cdot 1_{\{|d| \leq 1\}}$ where $d = \frac{X - c}{h}$
- $\hat{\beta}_c = (X'WX)^{-1} X'WY$
- Covariance matrix is $s^2 (X'WX)^{-1}$

. . .

```
loc.lin <- function(Y, X, c = 0, bw = sd(X)/2) {
    d <- (X - c)/bw
    W <- 3/4 * (1 - d^2) * (abs(d) < 1)
    W <- diag(W)
    X <- cbind(1, d)
    b <- solve(t(X) %*% W %*% X) %*% t(X) %*% W %*% Y
    sigma <- t(Y - X %*% b) %*% W %*% (Y - X %*% b)/(sum(diag(W) > 0) - 2)
    sigma <- solve(t(X) %*% W %*% X) * c(sigma)
    return(c(est = b[1], se = sqrt(diag(sigma))[1]))
}
```

Simulate some Data

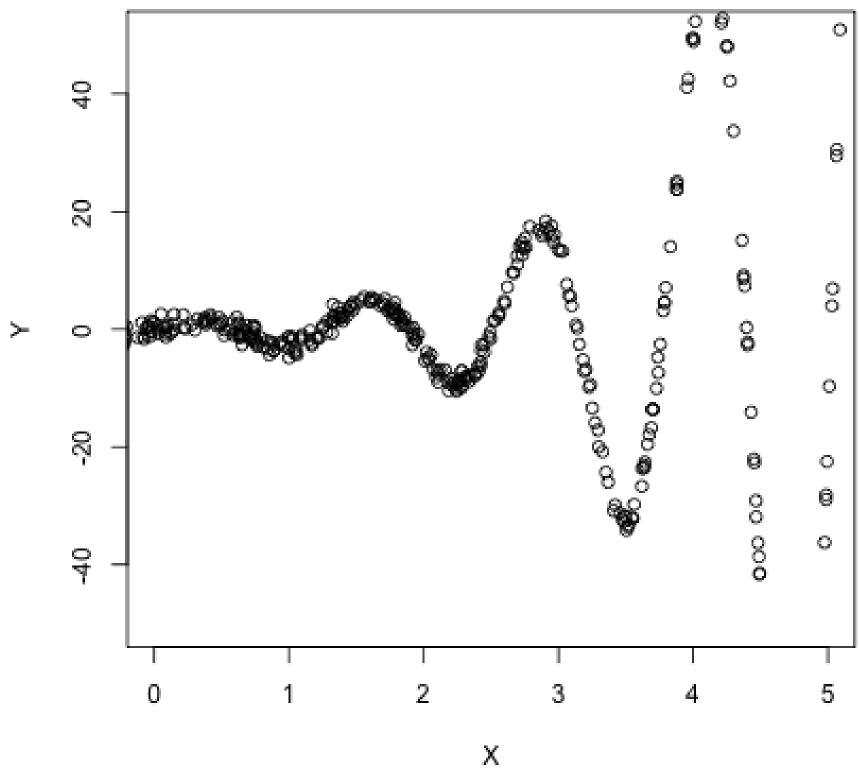
```
set.seed(1023)  # Important for replication
X <- rnorm(1000, 0, 5)
Y <- sin(5 * X) * exp(abs(X)) + rnorm(1000)
dat <- data.frame(X, Y)
plot(X, Y, xlim = c(0, 5), ylim = c(-50, 50))
```

Look at the Kernel

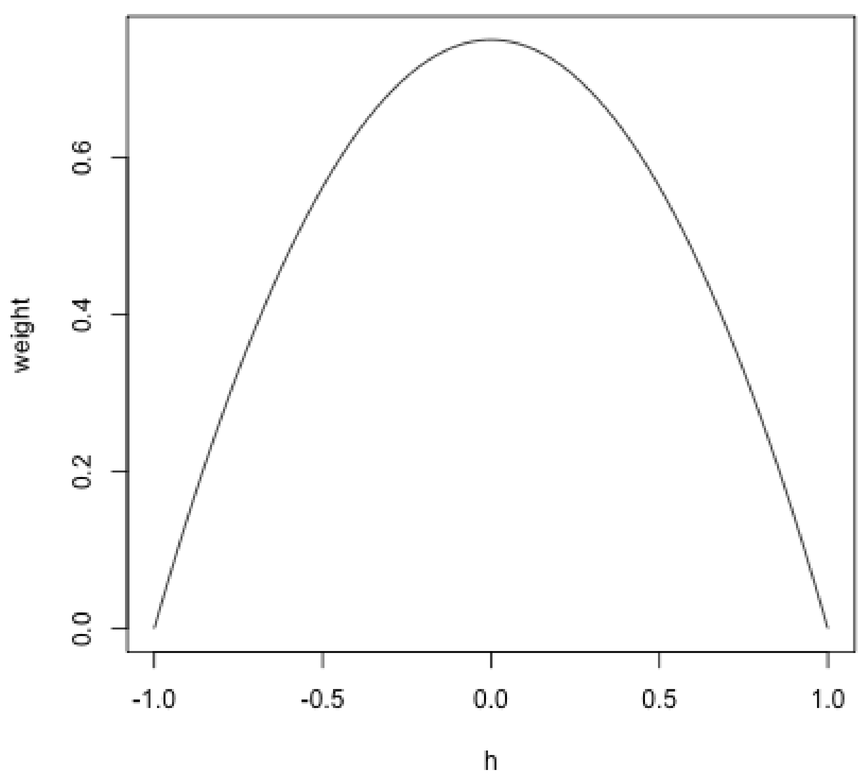
```
x <- seq(-1, 1, 0.01)
y <- 3/4 * (1 - x^2)
plot(x, y, type = "l", xlab = "h", ylab = "weight")
```

Fit the Surface

```
X.est <- seq(0, 5, 0.1)
dat.llm <- sapply(X.est, function(x) loc.lin(Y, X, c = x, bw = 0.25))
```

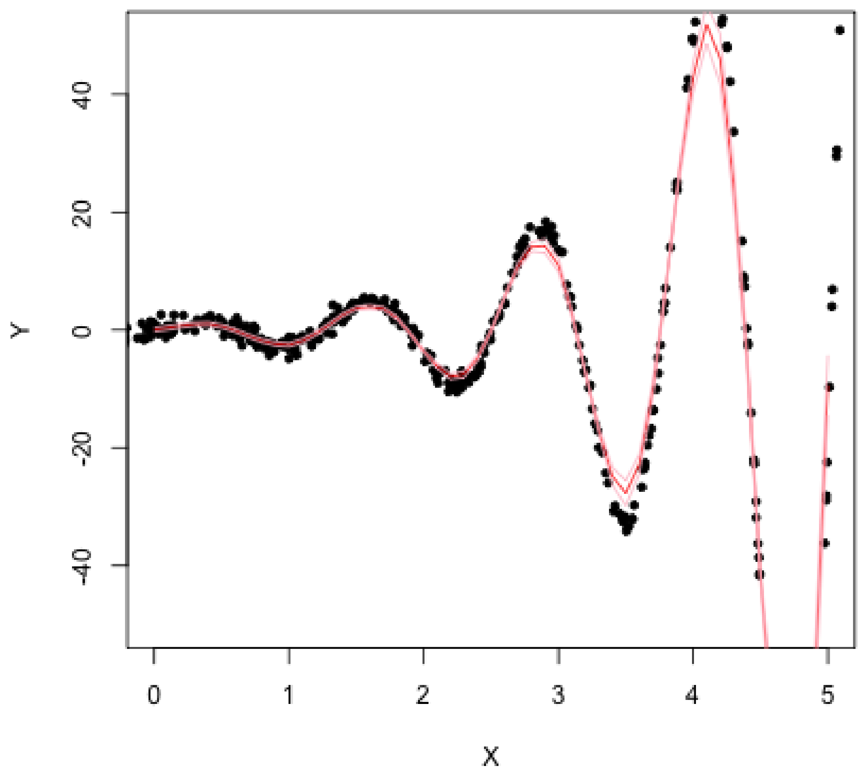


40
20
0
-20
-40
Y
0
1
2
3
4
5
X



weight
0.0
0.2
0.4
0.6
-1.0
-0.5
0.0
0.5
1.0
h

```
plot(X, Y, xlim = c(0, 5), ylim = c(-50, 50), pch = 20)
lines(X.est, dat.llm[1, ], col = "red")
lines(X.est, dat.llm[1, ] + 1.96 * dat.llm[2, ], col = "pink")
lines(X.est, dat.llm[1, ] - 1.96 * dat.llm[2, ], col = "pink")
```



Introduce Example

- We'll be working with data from a paper in the most recent issue of IO.
- Helfer, L.R. and E. Voeten. (2014) "International Courts as Agents of Legal Change: Evidence from LGBT Rights in Europe"
- The treatment we are interested in is the presence of absence of a ECtHR judgment.
- The outcome is the adoption of progressive LGBT policy.

- And there's a battery of controls, of course.
- Voeten has helpfully put all replication materials online.

Prepare example

```
require(foreign, quietly = TRUE)
d <- read.dta("replicationdataIOLGBT.dta")
# Base specification
d$ecthrpos <- as.double(d$ecthrpos) - 1
d.lm <- lm(policy ~ ecthrpos + pubsupport + ecthrcountry + lgbtlaws + cond +
    eumember0 + euemploy + coemembe + lngdp + year + issue + ccode, d)
d <- d[-d.lm$na.action, ]
d$issue <- as.factor(d$issue)
d$ccode <- as.factor(d$ccode)
summary(d.lm)$coefficients[1:11, ]
```

```
##                 Estimate Std. Error t value  Pr(>|t|)
## (Intercept)   -1.589e+00  4.956e-01 -3.2052 1.360e-03
## ecthrpos       6.501e-02  1.056e-02  6.1537 8.289e-10
## pubsupport     6.549e-03  2.743e-03  2.3877 1.700e-02
## ecthrcountry   1.297e-01  3.584e-02  3.6201 2.980e-04
## lgbtlaws       2.358e-02  6.281e-03  3.7548 1.759e-04
## cond           9.277e-02  1.796e-02  5.1657 2.509e-07
## eumember0     -8.586e-03  8.498e-03 -1.0105 3.123e-01
## euemploy       3.659e-03  1.269e-02  0.2883 7.731e-01
## coemembe       2.083e-02  7.277e-03  2.8623 4.227e-03
## lngdp         -7.522e-07  4.501e-07 -1.6711 9.477e-02
## year           8.020e-04  2.522e-04  3.1799 1.484e-03
```

Marginal Effects

- There has seemed to be a bit of confusion over marginal effects.
- The Blattman paper in HW3 uses marginal effects "well" in the sense of causal inference.
- The Huber et al. paper uses them in a very standard way, but perhaps not the way we'd want to think about them in THIS class.
- Use the builtin `predict` function; it will make your life easier.

. . .

```
d.lm.interact <- lm(policy ~ ecthrpos * pubsupport + ecthrcountry + lgbtlaws +
    cond + eumember0 + euemploy + coemembe + lngdp + year + issue + ccode, d)
```

```
frame0 <- frame1 <- model.frame(d.lm.interact)
frame0[, "ecthrpos"] <- 0
frame1[, "ecthrpos"] <- 1
meff <- mean(predict(d.lm.interact, newd = frame1) - predict(d.lm.interact,
    newd = frame0))
meff
```

```
## [1] 0.08197
```

- Why might this be preferable to "setting things at their means/medians"?
- It's essentially integrating over the sample's distribution of observed characteristics.
- (And if the sample is a SRS from the population [or survey weights make it LOOK like it is], this will then get you the marginal effect on the population of interest)

Delta Method

- Note 1: We know that our vector of coefficients are asymptotically multivariate normal.
- Note 2: We can approximate the distribution of many (not just linear) functions of these coefficients using the delta method.
- Delta method says that you can approximate the distribution of $h(b_n)$ with $\bigtriangledown h(b)'\Omega \bigtriangledown h(b)$ Where Ω is the asymptotic variance of b.
- In practice, this means that we just need to be able to derive the function whose distribution we wish to approximate.

Trivial Example

- We're interested in the ratio of the coefficient on `ecthrpos` to that of `pubsupport`.
- Call it $\frac{b_2}{b_3}$. The gradient is $(\frac{1}{b_3}, \frac{b_2}{b_3^2})$
- Estimate this easily in R with:

. . .

```
grad <- c(1/coef(d.lm)[3], coef(d.lm)[2]/coef(d.lm)[3]^2)
grad
```

```
## pubsupport   ecthrpos
##        334       8046
```

```r
se <- sqrt(t(grad) %*% vcov(d.lm)[2:3, 2:3] %*% grad)
est <- coef(d.lm)[2]/coef(d.lm)[3]
c(estimate = est, std.error = se)
```

```
## estimate.ecthrpos          std.error
##             24.09              35.33
```

```r
require(car)
deltaMethod(d.lm, "ecthrpos/pubsupport")
```

```
##                     Estimate    SE
## ecthrpos/pubsupport    24.09 35.55
```

Linear Functions

- But for most "marginal effects", you don't need to use the delta method.
- Just remember your rules for variances.
- $\text{var}(aX + bY) = a^2\text{var}(X) + b^2\text{var}(Y) + 2ab\text{cov}(X, Y)$
- If you are just looking at changes with respect to a single variable, you can just multiply standard errors.
- That is, a change in a variable of 3 units means that the standard error for the marginal effect would be 3 times the standard error of the coefficient.
- This isn't what Clarify does, though. It is weird.

Zelig for Marginal Effects

- (Zelig works like Clarify. [gee, I wonder why?])

. . .

```r
# install.packages('Zelig', repos='http://r.iq.harvard.edu', type='source')
require(Zelig, quietly = TRUE)
d.zg <- zelig(policy ~ ecthrpos * pubsupport + ecthrcountry + lgbtlaws + cond +
    eumember0 + euemploy + coemembe + lngdp + year + issue + ccode, d, model = "ls",
    cite = FALSE)
x0 <- setx(d.zg, ecthrpos = 0)
x1 <- setx(d.zg, ecthrpos = 1)
out <- sim(d.zg, x = x0, x1 = x1)
c(mean(out$qi$fd), meff)
```

```
## [1] 0.08150 0.08197
```

Sensitivity Analysis

- We're adding to Cyrus's discussion on post-treatment bias with a sensitivity analysis.
- This is also in Rosenbaum (1984), which he mentioned in class.
- The variable which one might think could induce post-treatment bias in our example is that of "public acceptance".

Rosenbaum Bounding

- In general Rosenbaum is a proponent of trying to "bound" biases.
- He does this in his "normal" sensitivity analysis method, and we do the same, here.
- We will assume a "surrogate" for U (necessary for CIA), which is observed post-treatment.
- The surrogate has two potential outcomes: S_1 and S_0
- It is presumed to have a linear response on the outcome.
- (As are the other observed covariates)
- This gives us the following two regression models: $E[Y_1|S_1 = s, X = x] = \mu_1 + \beta' x + \gamma' s$ and
  $E[Y_0|S_0 = s, X = x] = \mu_0 + \beta' x + \gamma' s$
- This gives us:
  $\tau = E[(\mu_1 + \beta' X + \gamma' S_1) - (\mu_0 + \beta' X + \gamma' S_0)]$
- Which is equal to the following useful expression:
  $\tau = \mu_1 - \mu_0 + \gamma'(E[S_1 - S_0])$
- For us, this means that $\tau = \beta_1 + \beta_2 E[S_1 - S_0]$

Back to example

- Our surrogate is public acceptance.
- But it can be swayed by court opinions, right? This is at least plausible.
- Let's try and get some reasonable bounds on τ.

. . .

```
sdS <- sd(d$pubsupport)
Ediff <- c(-1.5 * sdS, -sdS, -sdS/2, 0, sdS/2, sdS, 1.5 * sdS)
tau <- coef(d.lm)[2] + coef(d.lm)[3] * Ediff
names(tau) <- c("-1.5", "-1", "-.5", "0", ".5", "1", "1.5")
tau
```

```
##    -1.5      -1     -.5       0      .5       1     1.5 
## 0.06621 0.06818 0.07015 0.07212 0.07409 0.07606 0.07803 
```

- But with this method, you don't necessarily have to assume that the regression functions are this rigid.
- Can you think about how one might relax some assumptions?