Causality and biases

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Some hypotheses to consider

Newsworthiness

"It seems the most newsworthy scientific studies the least trustworthy." What could explain this?

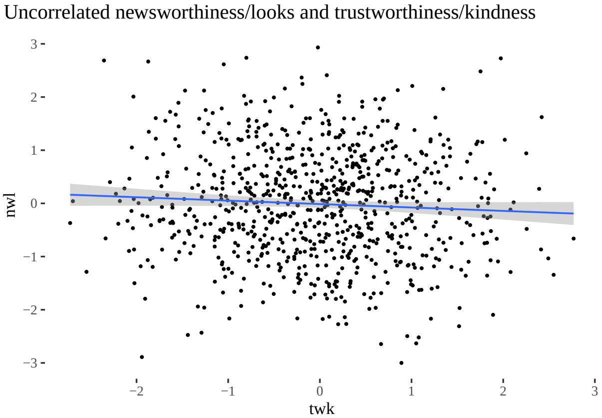
Jerks

"It seems good-looking men are jerks." What could explain this?

Selection-distortion effect

```r
N <- 800 #proposals/candidates
p <- .5  #proportion to select
# uncorrelated newsworthiness/looks and trustworthiness/kindness
nwl <- rnorm(N)
twk <- rnorm(N)
cor(nwl,twk)
```

```
## [1] -0.06152328
```



Selection-distortion effect

```
s <- nwl + twk # total score
q <- quantile( s , 1-p ) # top 10% threshold
selected <- ifelse( s >= q , TRUE , FALSE )
cor( twk[selected] , nwl[selected] )
```

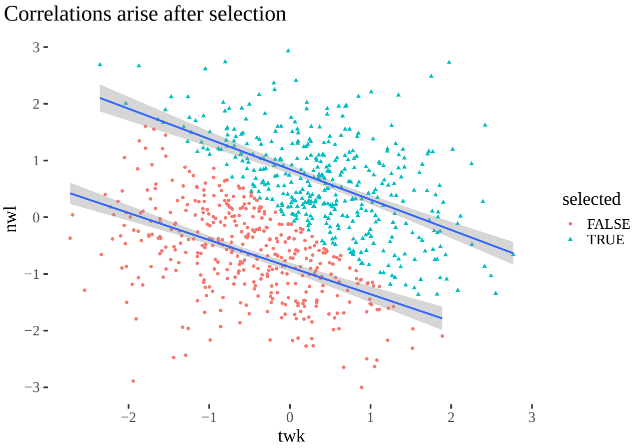
```
## [1] -0.5433415
```

```
cor( twk[!selected] , nwl[!selected] )
```

```
## [1] -0.5040041
```

Selection-distortion effect

```
ggplot() + geom_point(aes(
  x = twk, y = nwl, color = selected, shape = selected))+
geom_smooth(aes(
  x = twk, y = nwl, group = selected), method = "lm")+th+
  ggtitle("Correlations arise after selection")
```



Multiple regression will not save you

```r
news <- list(nwl = nwl, twk = twk,
             sel = as.integer(selected+1))

newsTWK <- quap(
  alist(
    nwl ~ dnorm( mu , sigma ) ,
    mu <- a + t * twk ,
    a ~ dnorm( 0 , 2 ) ,
    t ~ dnorm( 0 , .2 ) ,
    sigma ~ dexp( 1 )
  ) ,
  data= news )

precis(newsTWK)
```

```
##              mean         sd        5.5%        94.5%
## a     -0.01252908 0.03613758 -0.07028391  0.045225751
## t     -0.06223462 0.03627592 -0.12021054 -0.004258699
## sigma  1.02131620 0.02550846  0.98054875  1.062083648
```

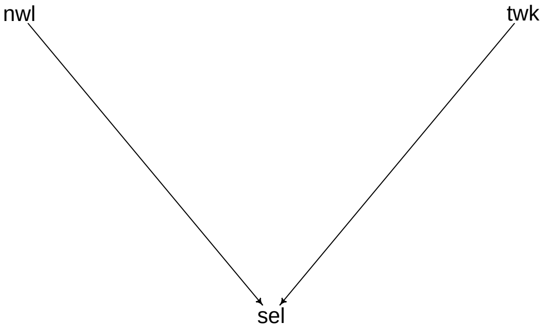
Multiple regression will not save you

```r
newsTWKselected <- quap(
  alist(
    nwl ~ dnorm( mu , sigma ) ,
    mu <- a[sel] + t[sel] * twk ,
    t[sel] ~ dnorm( 0 , .2 ) ,
    a[sel] ~ dnorm(0, 2),
    sigma ~ dexp( 1 )
  ) ,
  data= news )

precis(newsTWKselected, depth  = 2)
```

```
##              mean         sd       5.5%      94.5%
## t[1]   -0.4583950 0.04047583 -0.5230832 -0.3937068
## t[2]   -0.5129769 0.04012847 -0.5771100 -0.4488439
## a[1]   -0.8693598 0.04099812 -0.9348828 -0.8038369
## a[2]    0.8342353 0.03918357  0.7716123  0.8968582
## sigma   0.6967769 0.01741858  0.6689387  0.7246152
```

Collider bias

```r
newsDAG <- dagitty (
  "dag{
  nwl -> sel <- twk
  }"
)
coordinates(newsDAG) <- list(
  x=c(nwl=0,sel=1,twk=2) , y=c(nwl=0,sel=1,twk=0) )
drawdag(newsDAG, cex = 2,
        radius = 3, goodarrow = TRUE, xlim = c(-.2,2.2), ylim = c(-1.2,.2))
```



Post-treatment bias

Blindly tossing in predictors is never a good idea

```
set.seed(21)
# number of subjects
N <- 100
# simulate initial aggression levels
aggression0 <- rnorm(N,1,.4)
#simulate vaccine
vaccine <- rep( 0:1 , each=N/2)
#simulate fungus
cordyceps <- rbinom( N , size=1 , prob=0.95 - vaccine * 0.5 )
# assign vaccines and simulate cordyceps and aggression
aggression1 <- aggression0 + rnorm(N, 1.2 + 2 *cordyceps, .4)
# compose a clean data frame
d <- data.frame( aggression0=aggression0 , aggression1=aggression1 ,
                 vaccine=vaccine , cordyceps=cordyceps )
precis(d)[,-5]
```

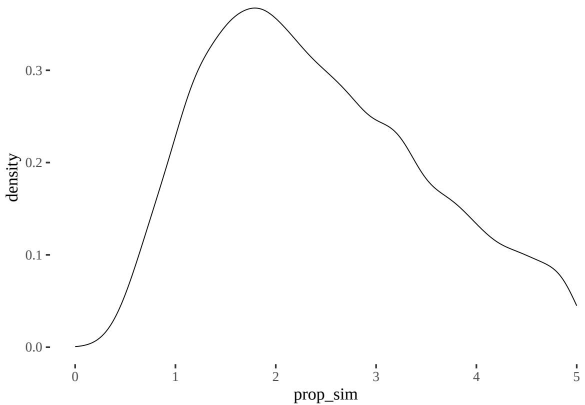
```
##                 mean        sd      5.5%    94.5%
## aggression0 1.028994 0.4108600 0.3452403 1.702803
## aggression1 3.703373 1.0376606 1.8749605 5.038115
## vaccine     0.500000 0.5025189 0.0000000 1.000000
## cordyceps   0.740000 0.4408440 0.0000000 1.000000
```

Choosing prior for proportional change

```
set.seed(23)
prop_sim <- rlnorm( 1e4 , .9 , .6 )
precis( data.frame(prop_sim) )[,-5]
```

```
##                mean       sd      5.5%    94.5%
## prop_sim 2.942808 1.890235 0.9431349 6.351591
```

```
ggplot()+geom_density(aes(x = prop_sim))+xlim(0,5)+th
```



Modeling aggression change

```r
set.seed(12)
aggressionModel <- quap(
  alist(
    aggression1 ~ dnorm( mu , sigma ),
    mu <- aggression0*p,
    p ~ dlnorm( .9 , 0.6 ),
    sigma ~ dexp( 1 )
  ), data=d )

precis(aggressionModel)[,-5]
```

```
##           mean         sd     5.5%    94.5%
## p     3.230631 0.12417941 3.032169 3.429094
## sigma 1.375921 0.09630769 1.222003 1.529840
```

Throwing in all predictors

```r
aggressionModelAll <- quap(
  alist(
    aggression1 ~ dnorm( mu , sigma ),
    mu <- aggression0 * p,
    p <-  a + bv*vaccine + bc*cordyceps,
    a ~ dnorm(1,2),
    bv ~ dnorm( 1 , 1 ),
    bc ~ dlnorm( .9 , 0.6 ),
    sigma ~ dexp( 1 )
  ), data=d )

precis(aggressionModelAll)[,-5]
```

```
##            mean        sd       5.5%     94.5%
## a     1.7361277 0.2838563  1.2824704 2.1897849
## bv    0.2785707 0.2290837 -0.0875492 0.6446906
## bc    1.8454706 0.2607080  1.4288088 2.2621323
## sigma 1.1118171 0.0779973  0.9871624 1.2364719
```

Throwing in all predictors

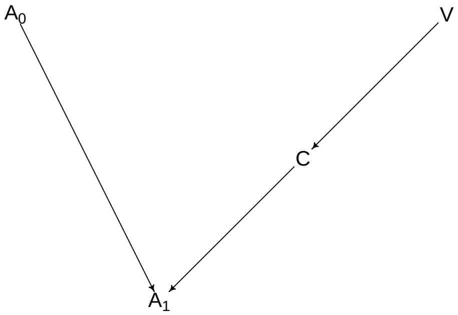
```r
aggressionModelVaccine <- quap(
  alist(
    aggression1 ~ dnorm( mu , sigma ),
    mu <- aggression0 * p,
    p <- a +   bv*vaccine,
    a ~ dnorm(1,2),
    bv ~ dnorm( 1 , 1 ),
    sigma ~ dexp( 1 )
  ), data=d )


precis(aggressionModelVaccine)[,-5]
```

```
##              mean         sd       5.5%      94.5%
## a       3.4774336 0.16402146  3.2152956  3.7395716
## bv     -0.5186644 0.23454769 -0.8935169 -0.1438119
## sigma   1.3340238 0.09356404  1.1844904  1.4835572
```

```r
cordyceps <- rbinom( N , size=1 , prob=0.95 - vaccine * 0.5 )
```

C d-separates V from A1

```
aggressionDAG <- dagitty( "dag {
A_0 -> A_1
C -> A_1
V -> C
}")
coordinates( aggressionDAG ) <- list( x=c(A_0=0,V=1.5,C=1,A_1=.5) ,
                                      y=c(A_0=0,V=0,C=.5,A_1=1) )
drawdag( aggressionDAG,  cex = 2, radius = 3, goodarrow = TRUE,
         xlim = c(-.3,1.7), ylim = c(-1.2,.2))
```



C d-separates V from A1

```
impliedConditionalIndependencies(aggressionDAG)
```

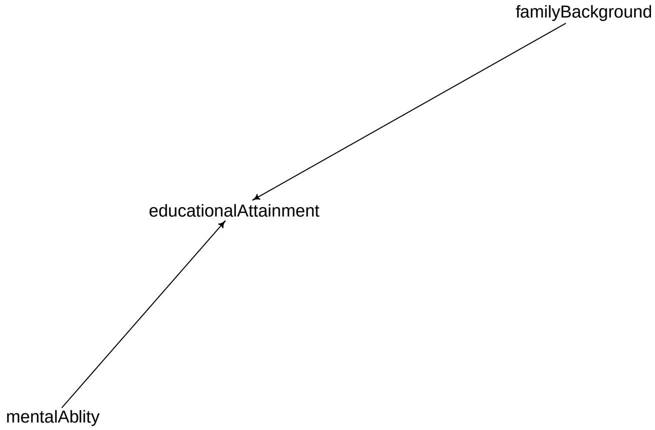
```
## A_0 _||_ C
## A_0 _||_ V
## A_1 _||_ V | C
```

The counterfactual model of data analysis

- individual: i
- potential outcomes: Y_i^0, Y_i^1 (only one observable)
- look at groups, with defendable assumptions estimate the **average effect**

Causality creeps

Example: status attainment tradition



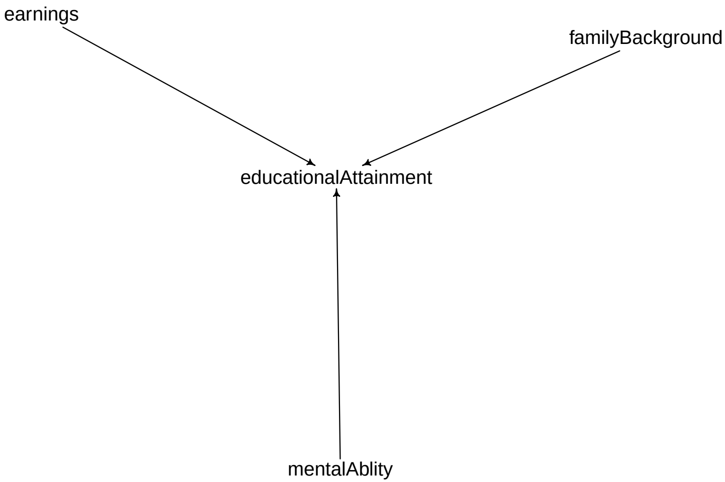
Implicit Wisconsin model

Students follow their own aspirations.

Causality creeps

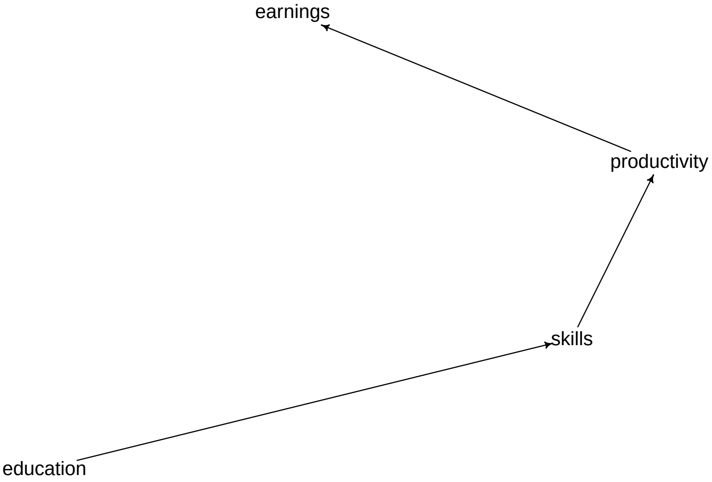
Critics

You can have all aspirations you want, resources will limit you



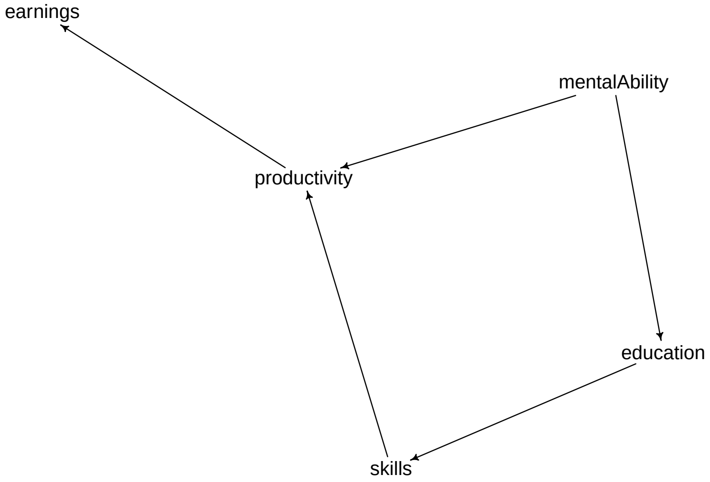
Causality creeps

Example: economic theory of human capital



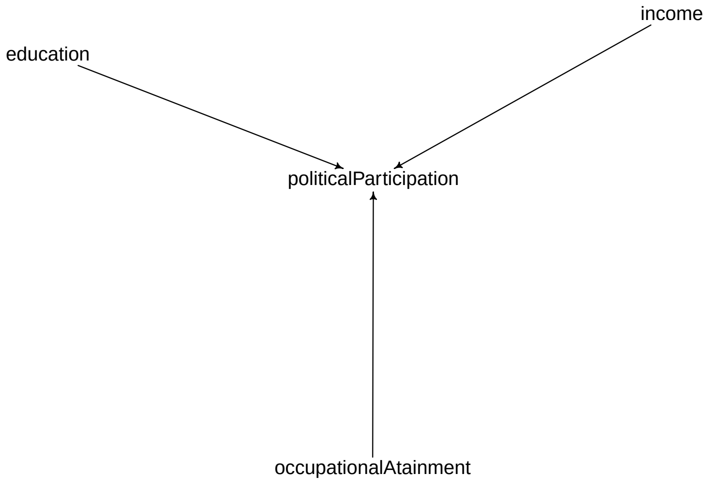
Causality creeps

Example: economic theory of human capital



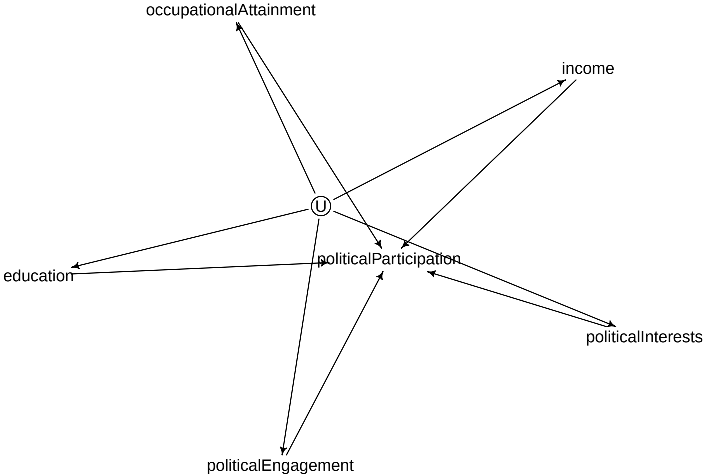
Causality creeps

Example: political participation



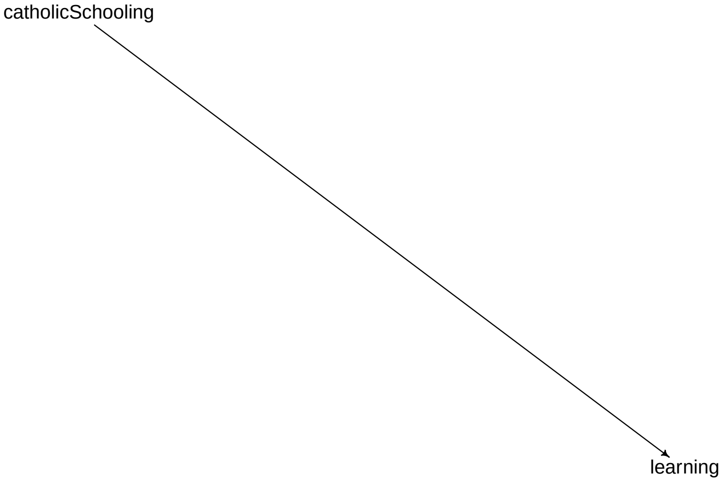
Causality creeps

Example: political participation



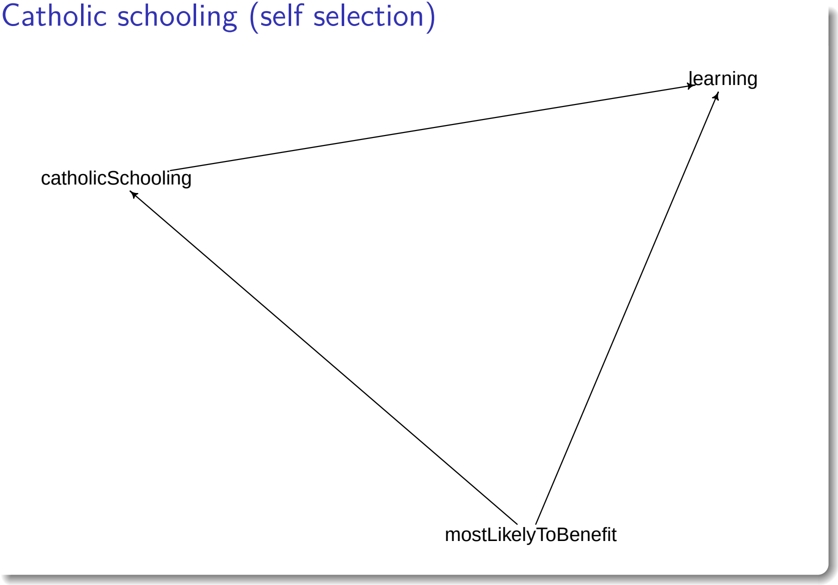
Causality creeps

Example: Catholic schooling



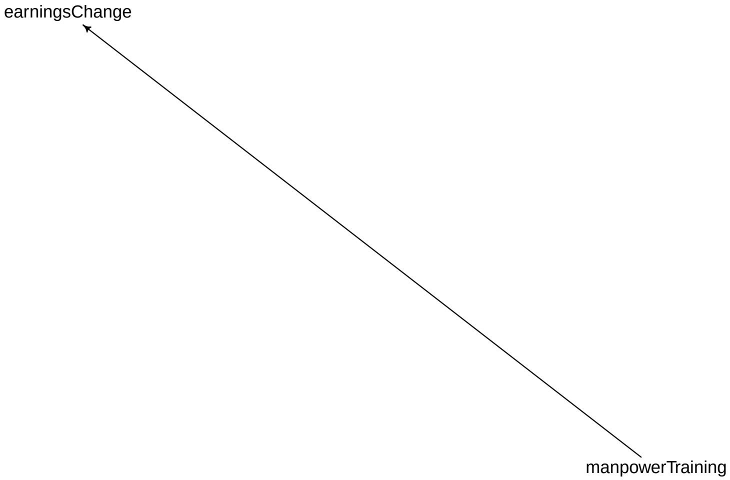
Causality creeps

Catholic schooling (self selection)



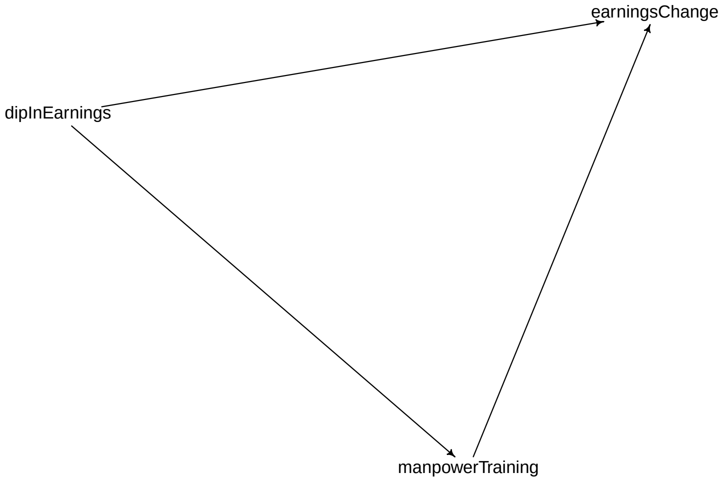
Causality creeps

Example: manpower training



Causality creeps

Manpower training (Ashenfelter's dip)



The straightforward solution

Randomize

Cut the arrows coming into the predictors.

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Randomize

Cut the arrows coming into the predictors.

The problem

- most data are observational
- randomization is often impossible, impractical, or unethical