

Blocking

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What?

Motivation: A Causal Inference Question

“Would a canvassing policy increase enrollment in a health insurance program?”

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Precinct	Party	Canvass?	Enroll %
1	Dem		
2	Dem		
3	Rep		
4	Rep		

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Suppose we observationally measure

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1	Dem	Yes	60
2	Dem	Yes	70
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4	Rep	No	30
Diff in Means: (Yes – No)			40

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Causal claims? Concerns?

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Seriously? Well, ...

```
x <- sample(0:1, size = 10, replace = TRUE)
```

```
x
```

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

Figure 1: Unlucky

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 - ▶ 10th \rightarrow control: $SE : \sqrt{\frac{5}{5} + \frac{5}{5}} = \sqrt{2}$

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- ▶ If $\text{Var}(Y_i(0)) = \text{Var}(Y_i(1))$, allocate units equally. Say 5 treated, 4 control. What to do with 10th village?
 - ▶ $10^{th} \rightarrow$ control: $SE : \sqrt{\frac{5}{5} + \frac{5}{5}} = \sqrt{2}$
 - ▶ $10^{th} \rightarrow$ treated: $SE : \sqrt{\frac{6}{4} + \frac{4}{6}} = \sqrt{2.66}$

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 - ▶ $10^{\text{th}} \rightarrow \text{treated}$: $SE : \sqrt{\frac{6}{4} + \frac{4}{6}} = \sqrt{2.66}$
- ▶ If $\text{Var}(Y_i(0)) \neq \text{Var}(Y_i(1))$, allocate \rightarrow higher-Variance condition

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Demonstration:

Unit	Y_0	Y_1 (+ cov)	Y_1 (- cov)
1	0	0	10
2	5	5	5
3	10	10	0
Means	5	5	5

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Suppose assign 1 to Tr, 2 to Co.

$$\widehat{ATE}_{+\text{cov}} = -7.5, 0, 7.5$$

$$\widehat{ATE}_{-\text{cov}} = 2.5, 0, -2.5 \text{ (less variance!)}$$

Example: Canvassing and Enrollment

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What would have happened to “No” precincts if “Yes”?

Example: Canvassing and Enrollment

But, is obs difference causal?

What do we really want to know?

Does canvassing actually change enrollment in precinct?
(Or, just Party \rightarrow Enrollment?)

What would have happened to “No” precincts if “Yes”?

What would have happened under other conditions?

Example: Canvassing and Enrollment

Suppose we can know both potential outcomes ...

Precinct	Party	Canvass?	Enroll % if No Canvass	Enroll % if Canvass
1	Dem	—	20	60
2	Dem	—	30	70
3	Rep	—	20	30
4	Rep	—	30	40
Means:			25	50

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$$\text{ATE} = 50 - 25 = 25$$

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Means:			25	50

$$\text{ATE} = 50 - 25 = 25$$

(True or an estimate?)

Example: Canvassing and Enrollment

Another way to think about same information:

Precinct	Party	Canvass?	Enroll % if No Canvass	Enroll % if Canvass	True Precinct Effect
1	Dem	—	20	60	40
2	Dem	—	30	70	40
3	Rep	—	20	30	10
4	Rep	—	30	40	10
Means:			25	50	25

$$\text{ATE} = (40 + 40 + 10 + 10)/4 = 25$$

The “Fundamental Problem of Causal Inference”

We can't observe both “Canvassed” and “Not Canvassed” for a precinct.

We can't observe both potential outcomes (counterfactuals).

So, how can we get a good causal estimate?

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Suppose we observe ...

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1	Dem	Yes		60
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Means:			25	65

$$\text{Estimated ATE} = 65 - 25 = 40$$

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Means:			25	65

Estimated ATE = $65 - 25 = 40$ ☹ (too big)

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Means:			30	45

$$\text{Estimated ATE} = 45 - 30 = 15$$

Example: Canvassing and Enrollment

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4	Rep	No	30	
Means:			30	45

Estimated ATE = $45 - 30 = 15$ ☹ (too small; closer)

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In our random allocation, possible data were

Assignments	Est ATE
YYNN	40

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$$E(\hat{\tau}) = \frac{1}{6} \cdot 40 + \frac{1}{6} \cdot 35 + \frac{1}{3} \cdot 25 + \frac{1}{6} \cdot 15 + \frac{1}{6} \cdot 10 = 25 = \bar{\tau}$$

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(unbiased)

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In practice, we don't know all potential outcomes.

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Two assignments (YYNN and NNYN) leave treatment perfectly confounded with party.

We can never see all of Y_1 , Y_0 . But we can see all of X !

Let's ensure X does not predict T .

A Solution

Blocking:

Creating pre-treatment groups that look same on predictors.

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(Then, randomize **within** groups.)

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Blocking:

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2	Dem	N	30	
3	Rep	N	20	
4	Rep	Y		40

(Then, randomize **within** groups.)

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Blocking restricts possible data to

Assignments	Est TE
YYNN	40
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Estimates have **less variance**, are **closer to true ATE**.

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Estimates have **less variance**, are **closer to true ATE**.

Under random allocation, 5 possible estimates: 40, 15, 25, 35, 10. Blocking **restricts** to 3 best: 15, 25, 35.

Example: Canvassing and Enrollment

Blocking restricts possible data to

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Why?

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- ▶ Triply-robust estimates: block, randomize, adjust

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- ▶ Increased **efficiency**
- ▶ Triply-robust estimates: block, randomize, adjust
- ▶ Block-level effects
 - ↪ different actors interested in different effects

Why do we block?

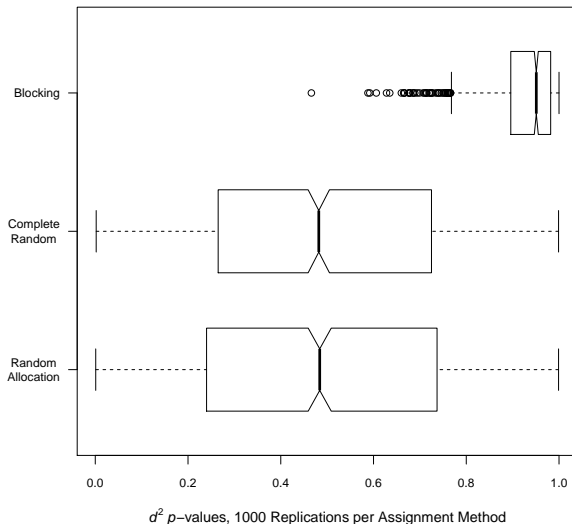
- ▶ Covariate **balance**
- ▶ Estimate **closer to truth**
- ▶ Increased **efficiency**
- ▶ Triply-robust estimates: block, randomize, adjust
- ▶ Block-level effects
 - ↪ different actors interested in different effects
- ▶ Guidelines for limited/uncertain resources

Why Block: Balance

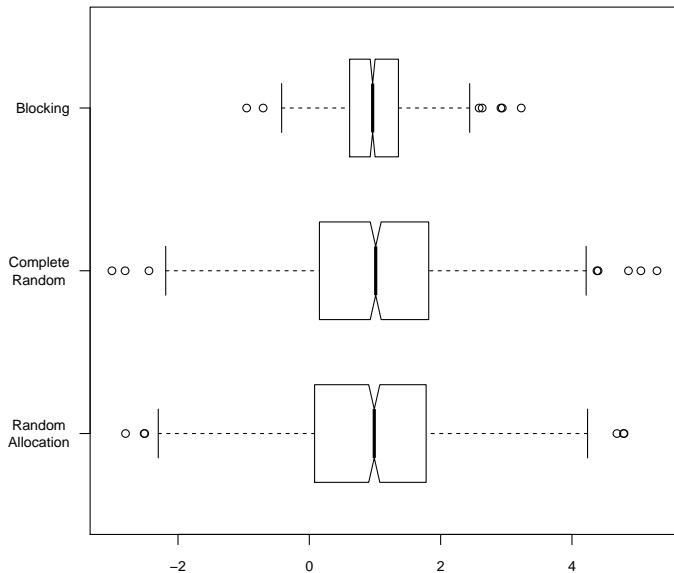
Simulation study: 100 units, $X_1 \sim N(0, 1)$, $X_2 \sim \text{Unif}(0, 1)$, $X_3 \sim \chi^2_2$; 1000 such experiments. Assg treatment in 3 ways.

Why Block: Balance

Simulation study: 100 units, $X_1 \sim N(0, 1)$, $X_2 \sim \text{Unif}(0, 1)$, $X_3 \sim \chi^2_2$; 1000 such experiments. Assg treatment in 3 ways.



Why Block: Efficiency

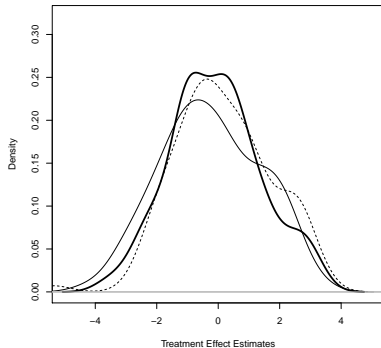
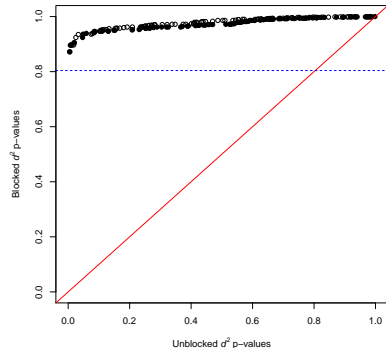


Blocking in Applications: Balance and Efficiency

Moore (2012): Perry Preschool Experiment

Left: QQ plot of balance (100 blocked vs. unblocked)

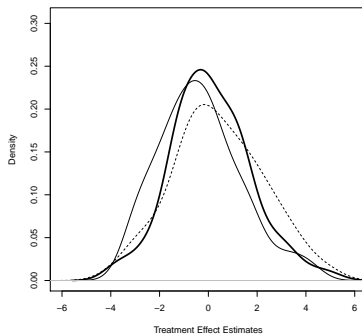
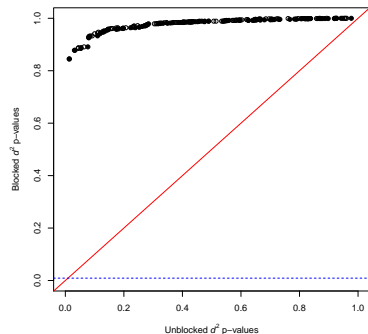
Right: Est TE under sharp null (100 blocked vs. unblocked)



(SES, sex, IQ)

Balance in Applications: Balance and Efficiency

Considering more variables ...



(+ siblings, AFDC, mom empl, educ, father, ...)

How: `blockTools`

Blocking with blockTools

Start with some sample data:

```
library(blockTools)
data(x100)
```

```
x100 |> head()
```

	id	id2	b1	b2	g	ig
1	1001	101	156	795	b	729
2	1002	102	813	469	a	627
3	1003	103	950	978	a	959
4	1004	104	991	781	a	661
5	1005	105	613	759	a	819
6	1006	106	654	838	b	643

(Moore 2012; Moore and Schnakenberg 2023)

Blocking with blockTools

```
b <- block(x100, id.vars = "id",  
           block.vars = c("b1", "b2"))
```

```
b1 <- b$blocks$`1`
```

```
b1 |> head()
```

	Unit 1	Unit 2	Distance
1	1043	1040	0.01240000
2	1100	1020	0.02259275
3	1065	1027	0.02912651
4	1085	1081	0.03498815
5	1088	1061	0.04789253
6	1064	1014	0.07985116

Blocking with blockTools

Why all this?

```
b1 <- b$blocks$`1`
```

We are extracting just the blocked pairs themselves.

► Why `b$blocks`? Since `b` has 3 components:

```
names(b)
```

```
[1] "blocks"      "level.two" "call"
```

► Why `blocks$1`? Since this is (default-named) first (and only) “group”:

```
names(b$blocks)
```

```
[1] "1"
```

Blocking with blockTools

What else could we do?

```
b_3groups_3conditions <- block(  
  x100,  
  groups = "g", # (Factor variable in data)  
  n.tr = 3,  
  id.vars = "id",  
  block.vars = c("b1", "b2"),  
  distance = "mve"  
)
```

```
b_3groups_3conditions$blocks
```

\$a

	Unit 1	Unit 2	Unit 3	Max Distance
1	1076	1039	1056	0.2509889
2	1065	1061	1002	0.4335040
3	1084	1058	1017	0.4373315
4	1050	1046	1081	0.4524767

Blocking with blockTools

Some rows from each “group”:

```
rows_a <- b_3groups_3conditions$blocks$a |> slice(1:2) |> mutate  
rows_b <- b_3groups_3conditions$blocks$b |> slice(1:2) |> mutate  
rows_c <- b_3groups_3conditions$blocks$c |> slice(1:2) |> mutate  
bind_rows(rows_a, rows_b, rows_c)
```

	Unit 1	Unit 2	Unit 3	Max Distance	group
1	1076	1039	1056	0.2509889	a
2	1065	1061	1002	0.4335040	a
3	1043	1040	1019	0.1664608	b
4	1048	1031	1062	0.2288718	b
5	1095	1092	1049	0.3778655	c
6	1045	1015	1082	0.3808569	c

Blocking with blockTools

Other arguments to `block()`

- ▶ `vcov.data`
- ▶ `groups`: for exact-blocks
- ▶ `n.tr`
- ▶ `id.vars`
- ▶ `block.vars`
- ▶ `algorithm`: `optGreedy`, `optimal`, `naiveGreedy`, `randGreedy`, `sortGreedy`
- ▶ `distance`: `mahalanobis`, `mcd`, `mve`, `euclidean`, $k \times k$ `matx`
- ▶ `weight`
- ▶ `level.two`: block states by most similar cities
- ▶ `valid.var`, `valid.range`: Goldilocks
- ▶ `seed.dist`: (for `mcd` and `mve`)

Assign

```
a <- assignment(b, seed = 71573706)
a
```

Assignments:

	Treatment 1	Treatment 2	Distance
1	1040	1043	0.01240000
2	1100	1020	0.02259275
3	1065	1027	0.02912651
4	1081	1085	0.03498815
5	1088	1061	0.04789253
6	1014	1064	0.07985116
7	1032	1070	0.08279625
8	1097	1098	0.08882421
9	1038	1018	0.09316331
10	1031	1048	0.10391953
11	1084	1058	0.10835825

Get Assignments

```
a |> extract_conditions(x100, id.var = "id")
```

```
[1] 2 1 2 2 2 2 1 2 2 1 1 1 1 1 1 2 2 1 2 2 2 1 2 1 1 2
[38] 1 1 1 2 2 2 2 2 2 1 2 1 2 2 2 2 1 1 2 1 2 1 1 2 2 1
[75] 1 2 2 2 1 2 1 1 1 1 2 1 2 1 1 2 1 2 1 1 2 2 1 2 1 1
```

```
x100 |> mutate(
  condition = extract_conditions(a, x100, id.var = "id"))
```

	id	id2	b1	b2	g	ig	condition
1	1001	101	156	795	b	729	2
2	1002	102	813	469	a	627	1
3	1003	103	950	978	a	959	2
4	1004	104	991	781	a	661	2
5	1005	105	613	759	a	819	2
6	1006	106	654	838	b	643	2
7	1007	107	640	645	c	12	1
8	1008	108	681	404	a	221	2

Assign 3 Conditions, within Groups

```
a3 <- assignment(b_3groups_3conditions, seed = 979677744)
a3
```

Assignments:

Group: a

	Treatment 1	Treatment 2	Treatment 3	Max Distance
1	1056	1076	1039	0.2509889
2	1002	1061	1065	0.4335040
3	1058	1084	1017	0.4373315
4	1046	1081	1059	0.4524767
5	1073	1098	1029	0.4599752
6	1060	1067	1004	0.5921446
7	1089	1024	1032	0.7554402
8	1052	1054	1030	0.8848444
9	1093	1026	1068	0.8975495
10	1036	1008	1091	1.3586913

How: randomizr

Blocking with `randomizr::block_ra()`

```
library(randomizr)

tr <- block_ra(x100$g)

# Better:

x100 |> mutate(tr = block_ra(x100$g))
```

	id	id2	b1	b2	g	ig	tr
1	1001	101	156	795	b	729	1
2	1002	102	813	469	a	627	1
3	1003	103	950	978	a	959	1
4	1004	104	991	781	a	661	1
5	1005	105	613	759	a	819	0
6	1006	106	654	838	b	643	1
7	1007	107	640	645	c	12	1
8	1008	108	681	404	a	221	0
9	1009	109	530	823	b	321	1

Then what?

blockTools: diagnose, get block IDs, check balance

Diagnose:

```
diagnose(a, data = x100, id.vars = "id",  
         suspect.var = "b1", suspect.range = c(0, 5))
```

blockTools: diagnose, get block IDs, check balance

Diagnose:

```
diagnose(a, data = x100, id.vars = "id",  
         suspect.var = "b1", suspect.range = c(0, 5))
```

Get block IDs

```
createBlockIDs(a, data = x100, id.var = "id")
```


blockTools: diagnose, get block IDs, check balance

Diagnose:

```
diagnose(a, data = x100, id.vars = "id",  
         suspect.var = "b1", suspect.range = c(0, 5))
```

Get block IDs

```
createBlockIDs(a, data = x100, id.var = "id")
```

Get balance:

```
assg2xBalance(a, x100, id.var = "id",  
              bal.vars = c("b1", "b2"))
```

Analysis

- ▶ Generally, use Lin or Blocked Diff-in-Means

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$$p_j(1 - p_j)n_j$$

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where

- ▶ p_j = share of block j treated
- ▶ n_j = size of block j
- ▶ (I.e., $p_j(1 - p_j) = \text{var}(TE)$ in block j)

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- ▶ n_j = size of block j
- ▶ (I.e., $p_j(1 - p_j) = \text{var}(TE)$ in block j)

Safer when

- ▶ p_j constant across blocks j
- ▶ n_j constant across blocks j

Analysis

```
library(estimatr)

df <- x100 |> mutate(tr = block_ra(x100$g))

lm_lin(b1 ~ tr, covariates = ~ g, data = df)
```

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	492.800000	39.08723	12.60769882	6.405020e-22
tr	-50.760000	51.70890	-0.98164922	3.287925e-01
gb_c	-4.673611	100.16089	-0.04666104	9.628824e-01
gc_c	-4.111111	92.84835	-0.04427770	9.647770e-01
tr:gb_c	-190.763889	129.80730	-1.46959290	1.450111e-01
tr:gc_c	-112.826389	128.65776	-0.87694974	3.827497e-01

DF

(Intercept)	94
tr	94
gb_c	94
gc_c	94

Analysis

Can I just ignore blocks and pool?

Analysis

Can I just ignore blocks and pool?

► If p_j varies, no

Thanks!

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References I

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