

Predictive algorithms: Introduction to an interactive workshop

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UCLA

Including past work with
Rebecca Johnson (Georgetown)
Brandon Stewart (Princeton)

and current work with
Kristin Liao (UCLA)

ilundberg.github.io/description

We acknowledge support through facilities and resources provided by the California Center for Population Research at UCLA (CCPR), which receives core support (P2C-HD041022) from the Eunice Kennedy Shriver National Institute of Child Health and Human Development (NICHD). The content is solely the responsibility of the authors and does not necessarily represent the official views of the Eunice Kennedy Shriver National Institute of Child Health & Human Development or the National Institutes of Health.

Plan for today

- ▶ Estimands in quantitative social science
- ▶ Descriptive estimands: A \hat{Y} view
- ▶ Intro to a computer tutorial

What Is Your Estimand? Defining the Target Quantity Connects Statistical Evidence to Theory

Ian Lundberg,^a  Rebecca Johnson,^b  and
Brandon M. Stewart^a 

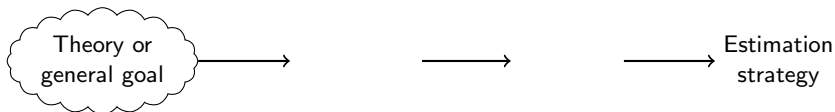
American Sociological Review
1–34

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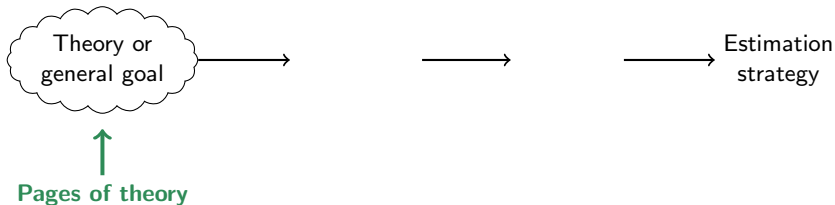
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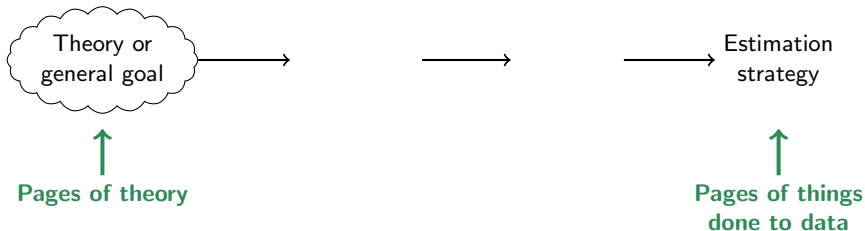
Research framework: Estimands connect theory to evidence



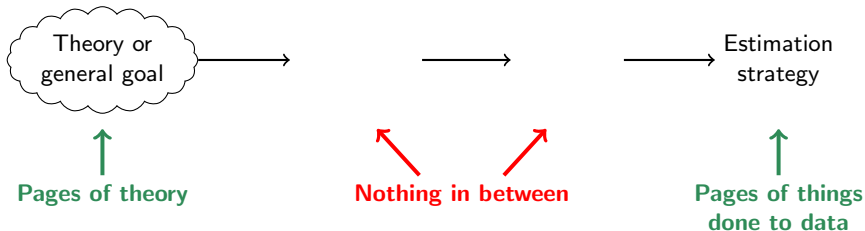
Research framework: Estimands connect theory to evidence



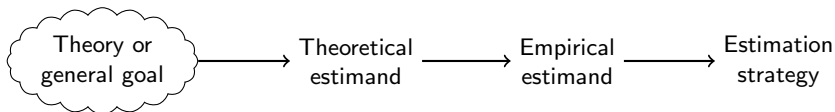
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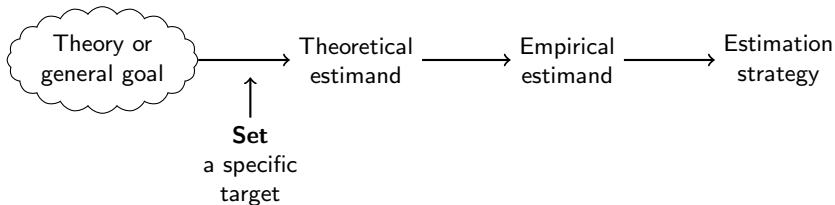
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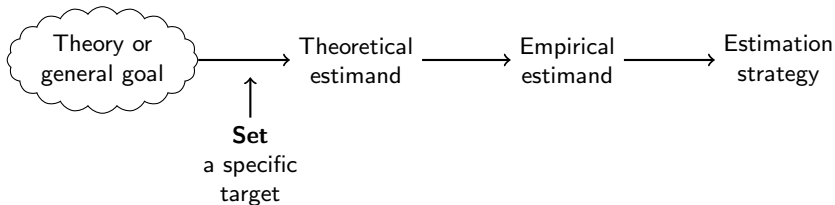
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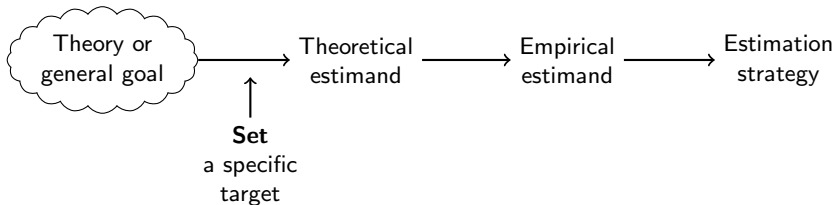
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Definition

A **unit-specific quantity**
aggregated over a
target population

Research framework: Estimands connect theory to evidence



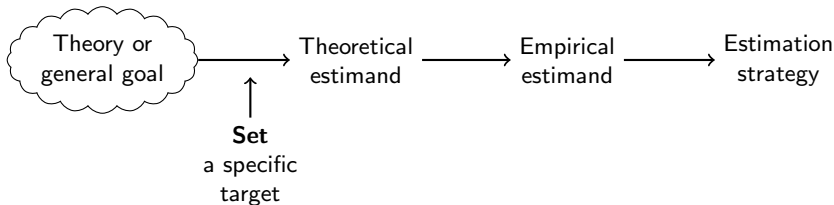
Definition

A **unit-specific quantity**
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Example

$$\frac{1}{\text{Size of U.S. adult population}} \sum_{i \text{ in U.S. adult population}} \left(\text{Employed}_i \right)$$

Research framework: Estimands connect theory to evidence



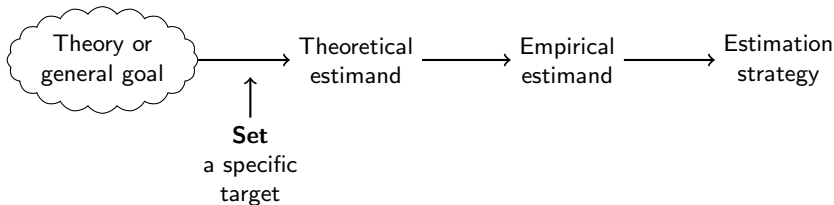
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Example

$$\frac{1}{\text{Size of U.S. adult population}} \sum_{i \text{ in U.S. adult population}} \left(\underbrace{\text{Employed}_i(\text{Job training})}_{\text{Employment if received job training}} - \underbrace{\text{Employed}_i(\text{No job training})}_{\text{Employment if did not receive job training}} \right)$$

Research framework: Estimands connect theory to evidence



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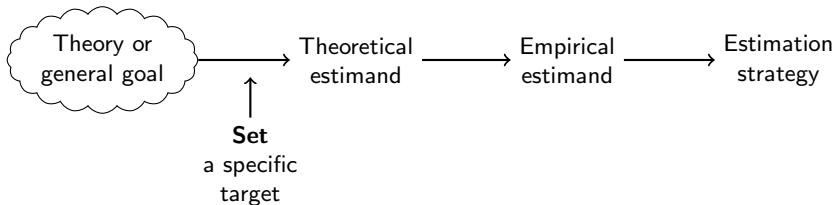
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Liebersen 1987, Abbott 1988, Freedman 1991, Xie 2013, Hernán 2018

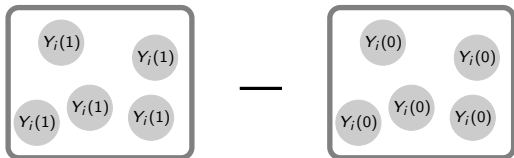
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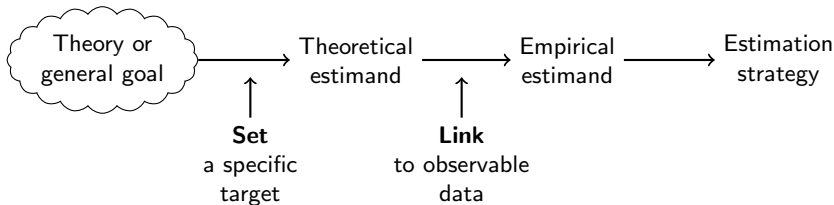
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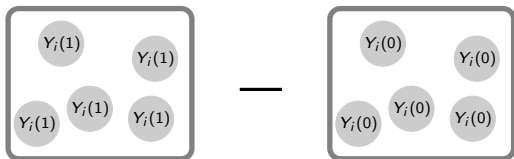
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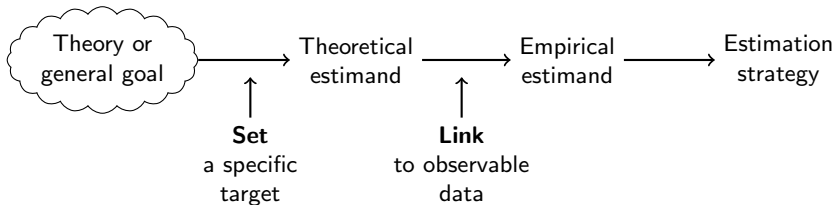
Definition

A quantity involving
observable data

Example



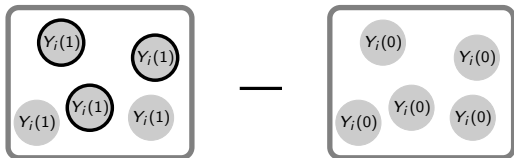
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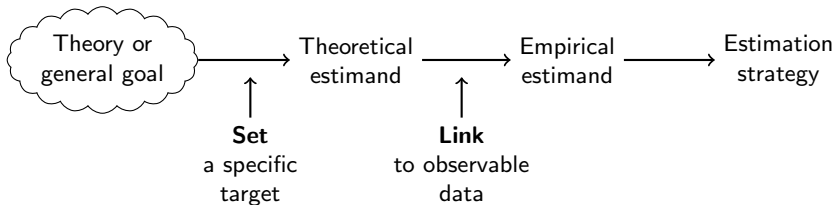
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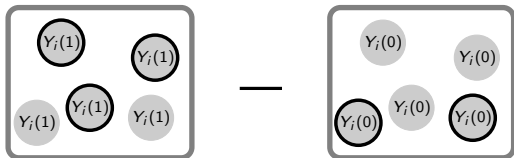
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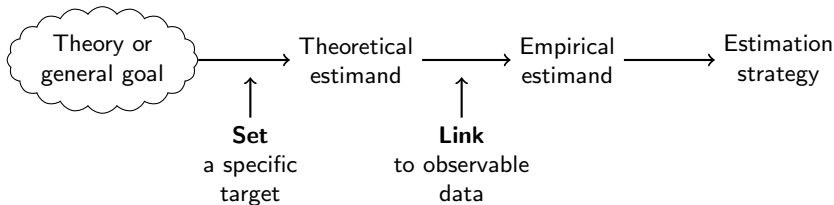
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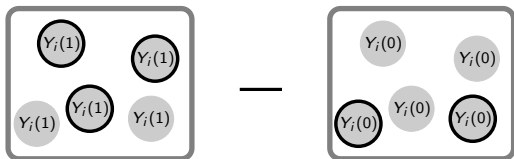
Research framework: Estimands connect theory to evidence



Definition

A quantity involving
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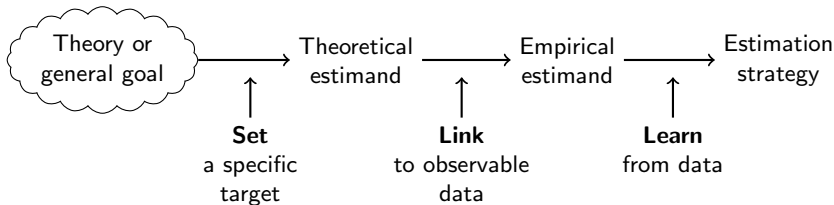
Example



$$\vec{X} \begin{matrix} \xrightarrow{\quad} T \xrightarrow{\quad} Y \\ \quad \quad \quad \searrow \quad \quad \nearrow \end{matrix}$$

Pearl 2009, Imbens and Rubin 2015,
Morgan and Winship 2015, Elwert and Winship 2014

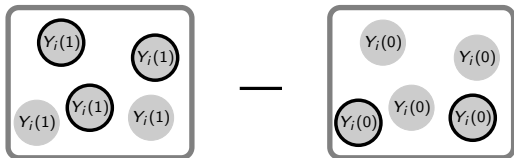
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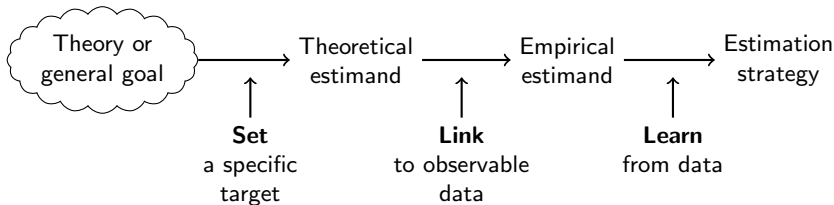
Definition

An algorithm applied to data

Example



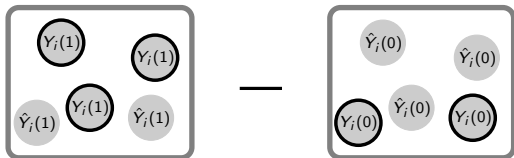
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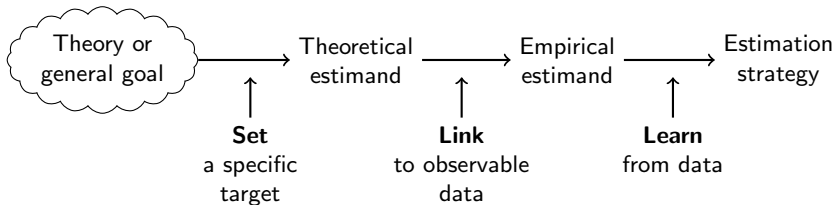
Definition

An algorithm applied to data

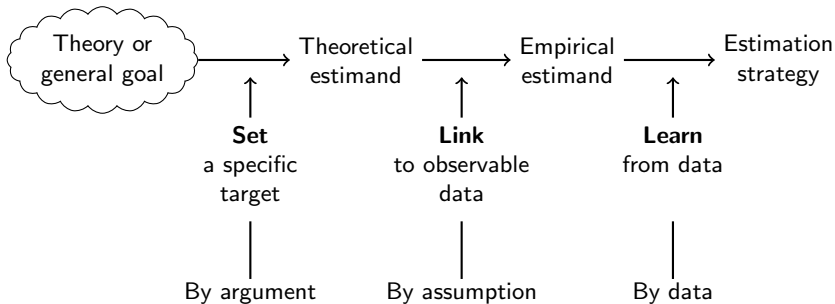
Example

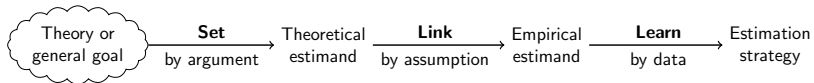


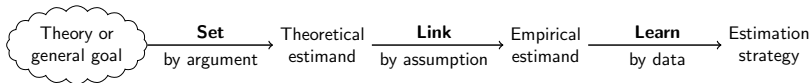
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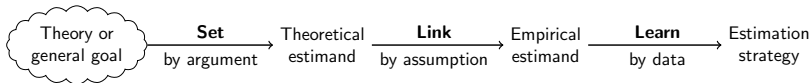
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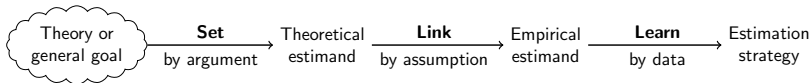


Effect of motherhood
on employment



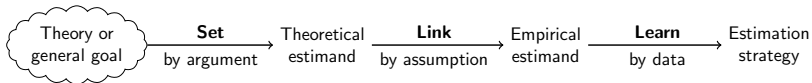
Effect of motherhood
on employment

First two births
are the same sex

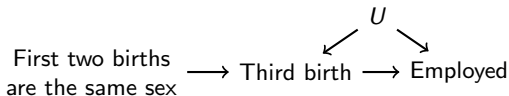


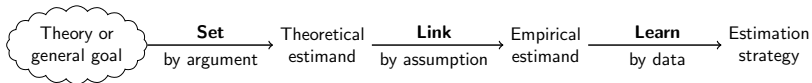
Effect of motherhood
on employment

First two births
are the same sex → Third birth



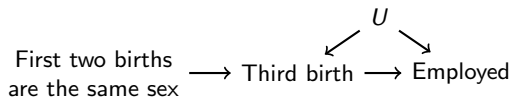
Effect of motherhood
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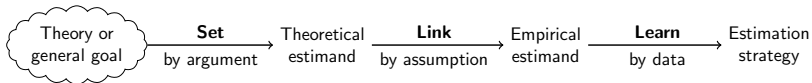




Vague estimand

Effect of motherhood
on employment

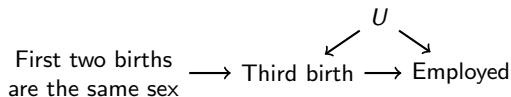


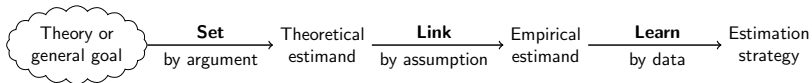


Vague estimand

Effect of motherhood
on employment

Precise estimand





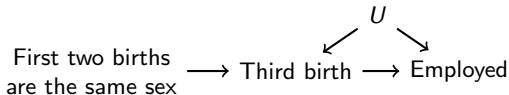
Vague estimand

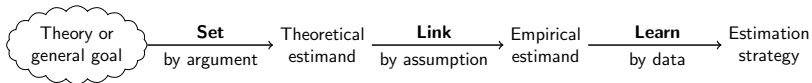
Effect of motherhood
on employment

Precise estimand

Effect of having **3 vs. 2 children**

**unit-specific
quantity**





Vague estimand

Effect of motherhood on employment

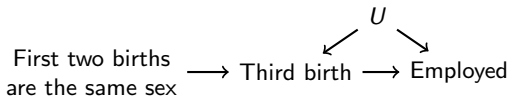
target population

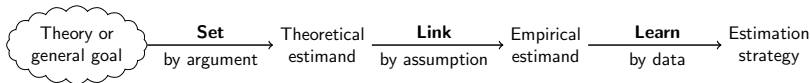


Precise estimand

Effect of having 3 vs. 2 children

among those with at least two children who would have a third birth if and only if the first two were of the same sex

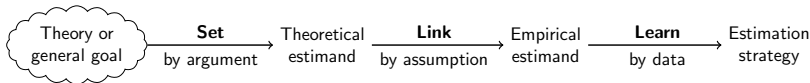




Precise estimand

Effect of having 3 vs. 2 children
among those with at least two children who
would have a third birth if and only if the
first two were of the same sex

$\approx 4\%$ of all mothers



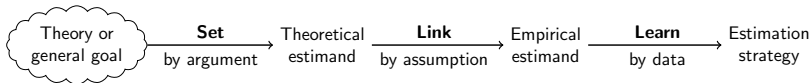
Precise estimand

Effect of having 3 vs. 2 children
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You have to argue either:

- 1)
- 2)



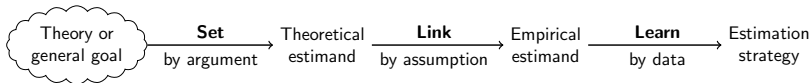
Precise estimand

Effect of having 3 vs. 2 children
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You have to argue either:

- 1) That estimand matters for theory, or
- 2)



Precise estimand

Effect of having 3 vs. 2 children
among those with at least two children who
would have a third birth if and only if the
first two were of the same sex

$\approx 4\%$ of all mothers

You have to argue either:

- 1) That estimand matters for theory, or
- 2) It speaks to some broader estimand



1. Set the target quantity.



Describe a population

What is the proportion employed
among U.S. resident women ages 21–35?



Describe a population

What is the proportion employed
among U.S. resident women ages 21–35?

Woman 1

Woman 2

Woman 3

Woman 4



Describe a population

What is the proportion employed
among U.S. resident women ages 21–35?

	<u>Employed?</u>
Woman 1	1
Woman 2	0
Woman 3	1
Woman 4	1



Describe population subgroups

What is the proportion employed among U.S. resident women ages 21–35, comparing mothers to non-mothers?



Describe population subgroups

What is the proportion employed among U.S. resident women ages 21–35, comparing mothers to non-mothers?

	<u>Employed?</u>		<u>Employed?</u>
Mother 1	0	Non-Mother 1	1
Mother 2	0	Non-Mother 2	0
Mother 3	0	Non-Mother 3	1
Mother 4	1	Non-Mother 4	1



Causal effect in a population

What is the causal effect of motherhood on employment among U.S. resident women ages 21–35?



Causal effect in a population

What is the causal effect of motherhood on employment among U.S. resident women ages 21–35?

Woman 1

Woman 2

Woman 3

Woman 4



Causal effect in a population

What is the causal effect of motherhood on employment among U.S. resident women ages 21–35?

	Would be employed if a mother? $Y(1)$
Woman 1	0
Woman 2	0
Woman 3	0
Woman 4	1



Causal effect in a population

What is the causal effect of motherhood on employment among U.S. resident women ages 21–35?

	Would be employed if a mother? $Y(1)$	Would be employed if a non-mother? $Y(0)$
Woman 1	0	1
Woman 2	0	0
Woman 3	0	1
Woman 4	1	1



Causal effect in a population

What is the causal effect of motherhood on employment among U.S. resident women ages 21–35?

	Would be employed if a mother? $Y(1)$	Would be employed if a non-mother? $Y(0)$	Causal effect $Y(1) - Y(0)$
Woman 1	0	1	-1
Woman 2	0	0	0
Woman 3	0	1	-1
Woman 4	1	1	0

Why model?

Causal effect in a population

What is the causal effect of motherhood on employment among U.S. resident women ages 21–35?

	Would be employed if a mother? $Y(1)$	Would be employed if a non-mother? $Y(0)$	Causal effect $Y(1) - Y(0)$
Woman 1	0	1	-1
Woman 2	0	0	0
Woman 3	0	1	-1
Woman 4	1	1	0

Why model?

Causal effect in a population

What is the causal effect of motherhood on employment among U.S. resident women ages 21–35?

	Would be employed if a mother? $Y(1)$	Would be employed if a non-mother? $Y(0)$	Causal effect $Y(1) - Y(0)$
Woman 1	?	1	?
Woman 2	?	0	?
Woman 3	0	?	?
Woman 4	1	?	?

Why model?

Describe population subgroups

What is the proportion employed among U.S. resident women ages 21–35, comparing mothers to non-mothers?

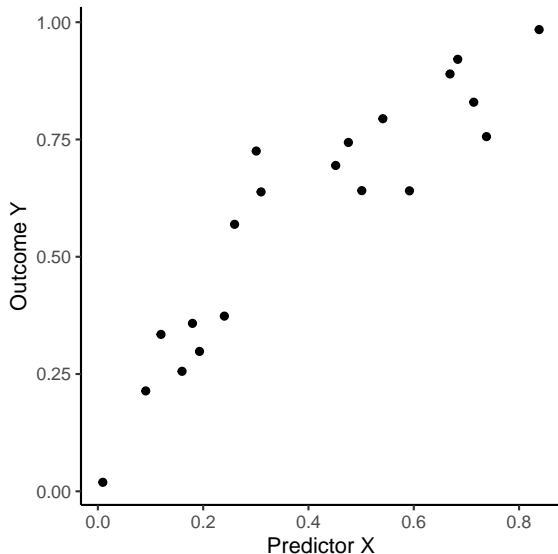
	<u>Employed?</u>		<u>Employed?</u>
Mother 1	0	Non-Mother 1	1
Mother 2	0	Non-Mother 2	0
Mother 3	0	Non-Mother 3	1
Mother 4	1	Non-Mother 4	1

A \hat{Y} view of description

With Kristin Liao, UCLA

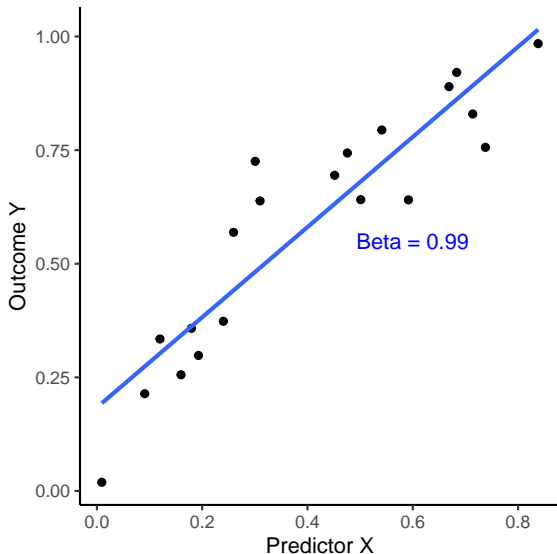
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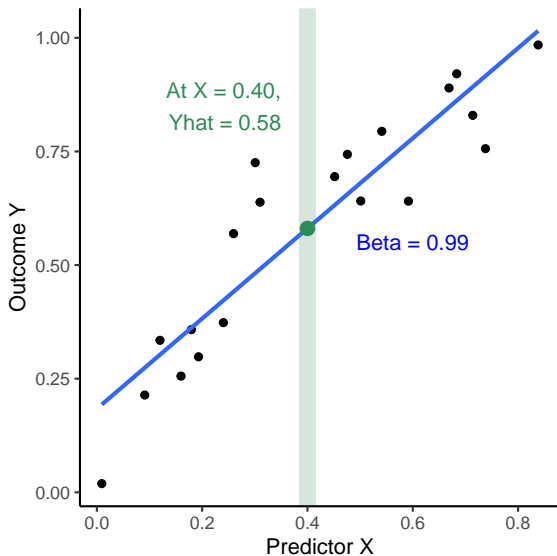
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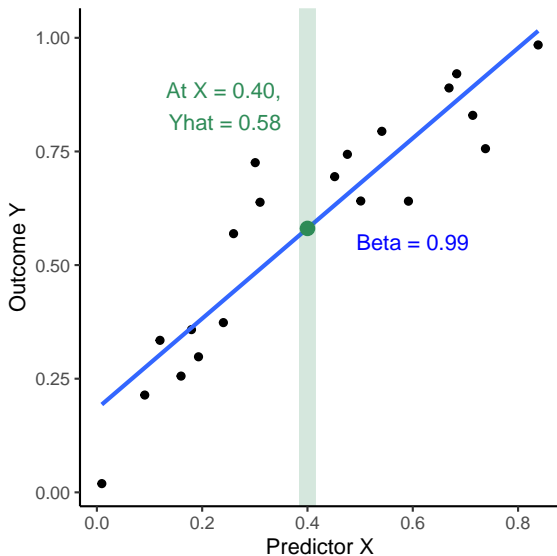
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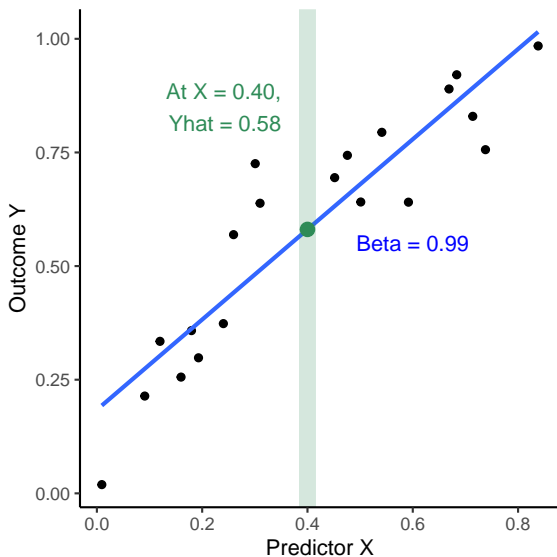
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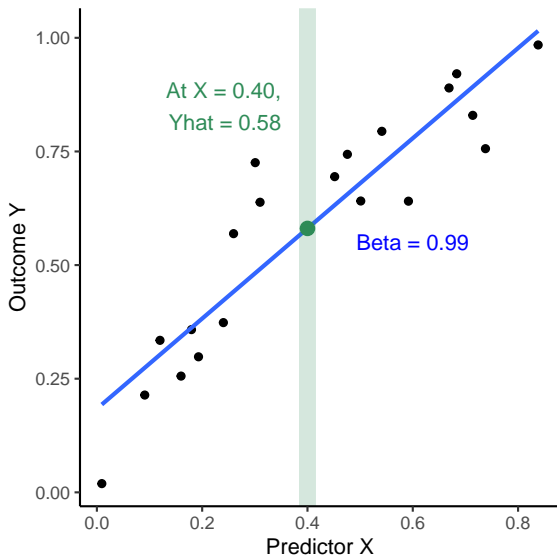
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Why model?

A \hat{Y} view of description

With Kristin Liao, UCLA

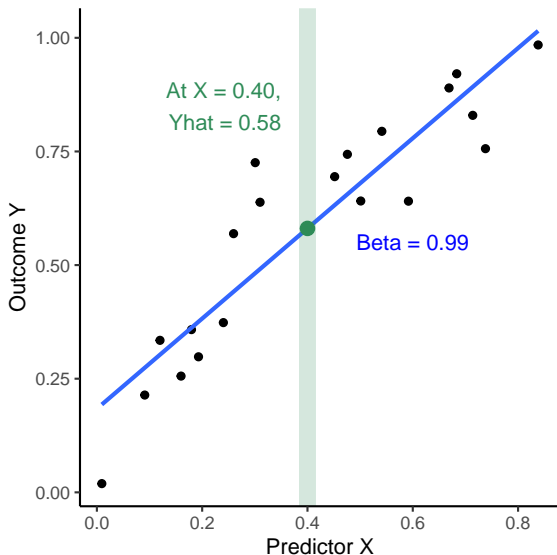


Why model?

A subgroups may have few units

A \hat{Y} view of description

With Kristin Liao, UCLA



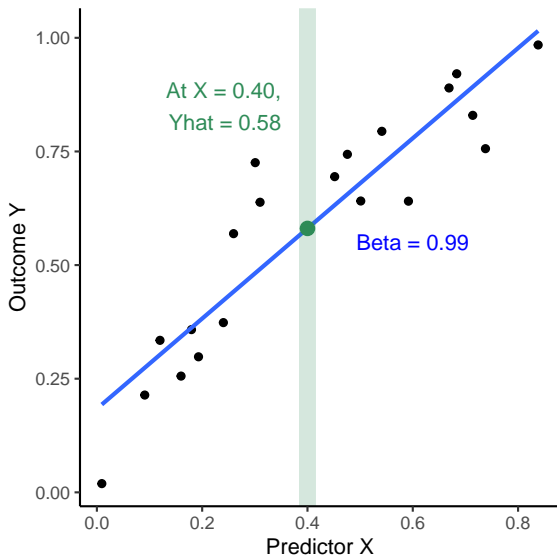
Why model?

A subgroups may have few units

Model pools information across subgroups

A \hat{Y} view of description

With Kristin Liao, UCLA



Why model?

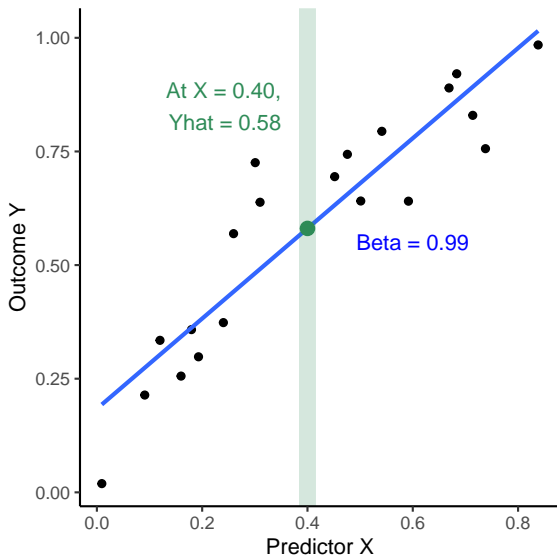
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Model pools information across subgroups

Report \hat{Y} , not $\hat{\beta}$

A \hat{Y} view of description

With Kristin Liao, UCLA



Why model?

A subgroups may have few units

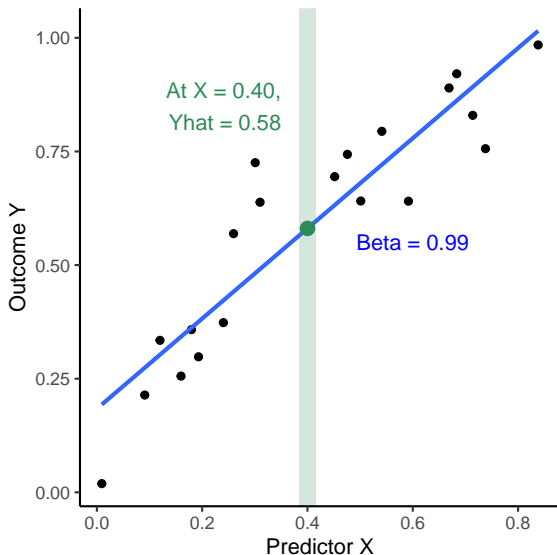
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Benefits

A \hat{Y} view of description

With Kristin Liao, UCLA



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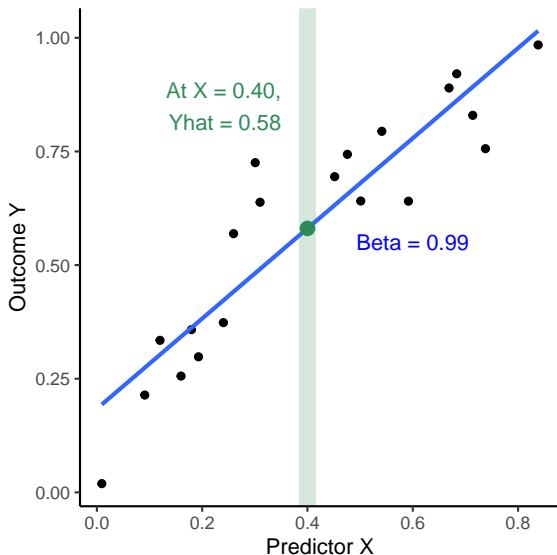
Report \hat{Y} , not $\hat{\beta}$

Benefits

Jargon-free results

A \hat{Y} view of description

With Kristin Liao, UCLA



Why model?

A subgroups may have few units

Model pools information across subgroups

Report \hat{Y} , not $\hat{\beta}$

Benefits

Jargon-free results

Plug in machine learning

Concrete exercise: Sex gap in pay

ilundberg.github.io/description

Sample of 5 million cases (true nonparametric estimates)

Simulate a sample of 100 (evaluate sample-based estimators)

Concrete exercise: Sex gap in pay

ilundberg.github.io/description

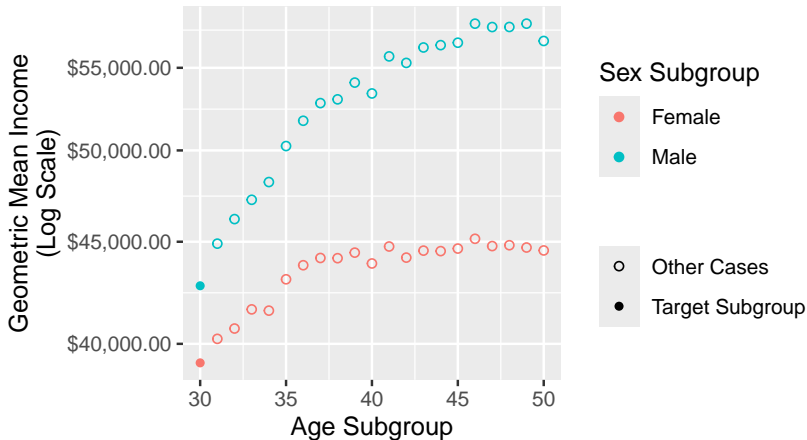
Source of 5 million cases

- ▶ American Community Survey (ACS) 2010–2019
- ▶ Adults age 30–50
- ▶ Worked 35+ hours per week in 50+ weeks last year
- ▶ Outcome: Annual wage and salary income

Concrete exercise: Sex gap in pay

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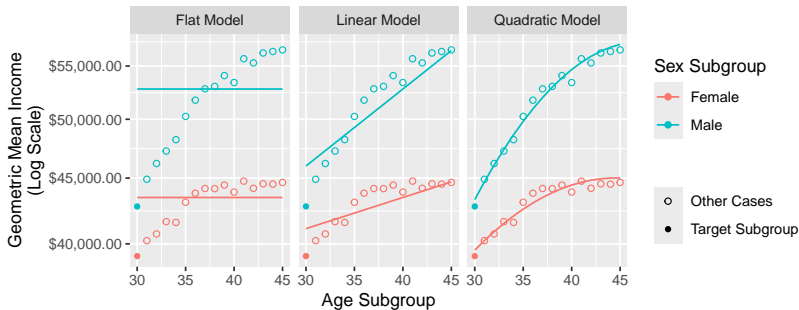
Illustrated on full data: 5 million cases



Concrete exercise: Sex gap in pay

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Illustrated on full data: 5 million cases

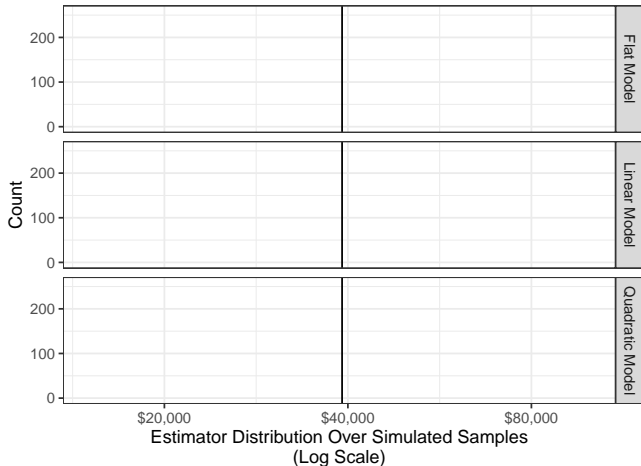


Evaluate models

ilundberg.github.io/description

Estimator Performance: Histogram Over Simulations

Estimand: Geometric mean income among 30-year-old female subgroup

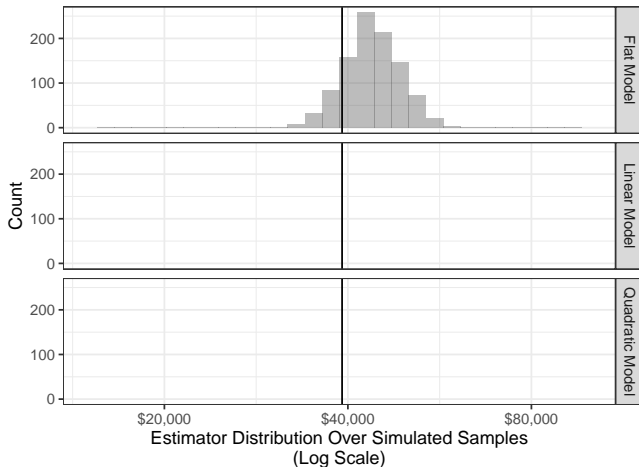


Evaluate models

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Estimator Performance: Histogram Over Simulations

Estimand: Geometric mean income among 30-year-old female subgroup

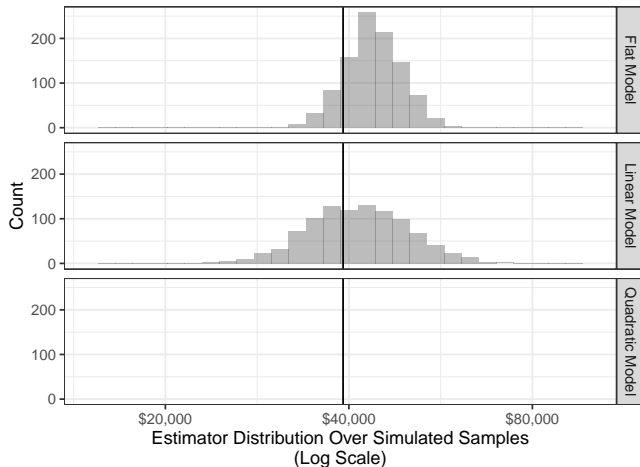


Evaluate models

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Estimator Performance: Histogram Over Simulations

Estimand: Geometric mean income among 30-year-old female subgroup

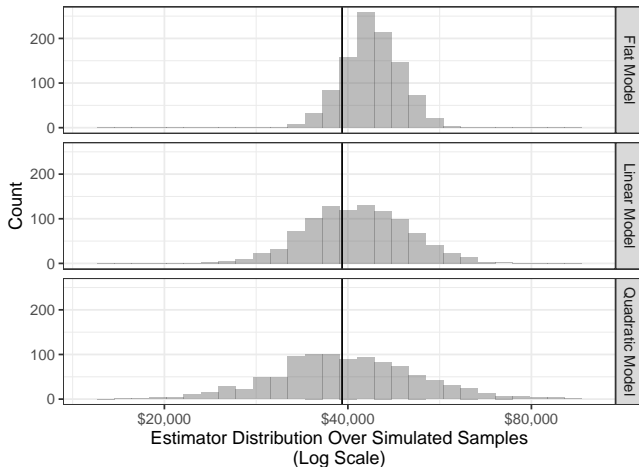


Evaluate models

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Estimator Performance: Histogram Over Simulations

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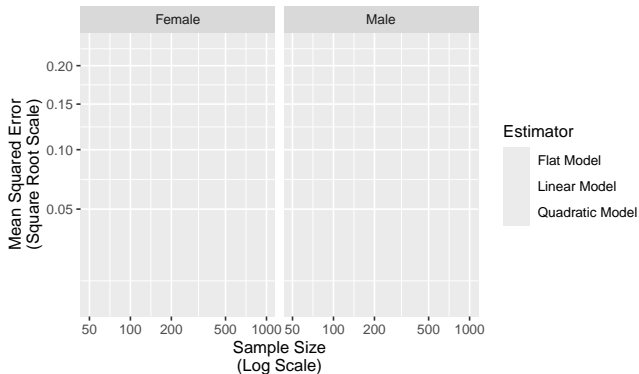


Evaluate models

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Best Estimator Depends on Estimand and Sample Size

Estimand: Geometric mean income among U.S. adults age 30

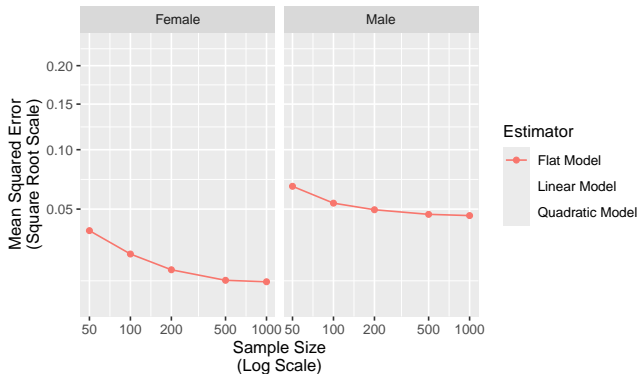


Evaluate models

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Best Estimator Depends on Estimand and Sample Size

Estimand: Geometric mean income among U.S. adults age 30

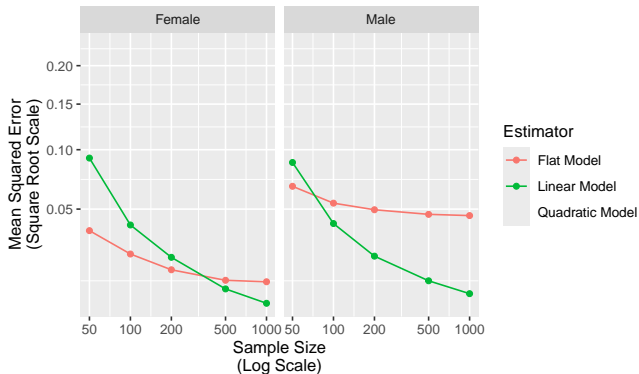


Evaluate models

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Best Estimator Depends on Estimand and Sample Size

Estimand: Geometric mean income among U.S. adults age 30

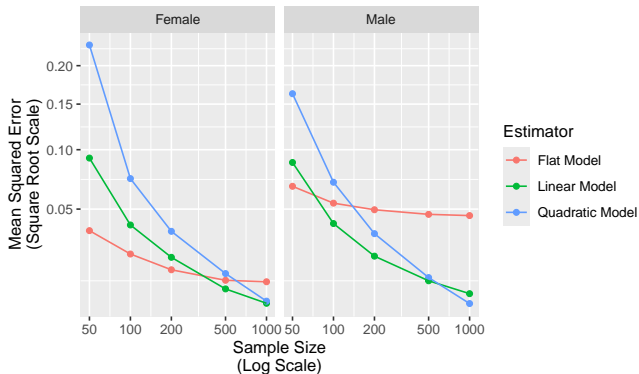


Evaluate models

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Best Estimator Depends on Estimand and Sample Size

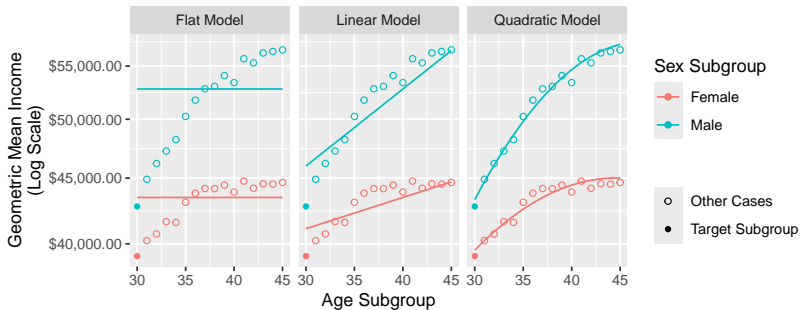
Estimand: Geometric mean income among U.S. adults age 30



Evaluate models

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Illustrated on full data: 5 million cases



Implications of a \hat{Y} view of description

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Implications of a \hat{Y} view of description

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- ▶ a model as a means to an end
 - ▶ we would rather not model
 - ▶ model only when you lack data

Implications of a \hat{Y} view of description

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- ▶ a model as a means to an end
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 - ▶ flat model was best

(lower variance)

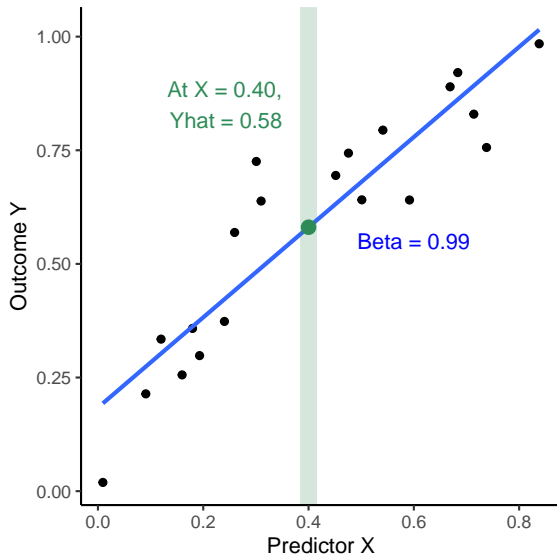
Implications of a \hat{Y} view of description

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- ▶ a model as a means to an end
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 - ▶ model only when you lack data
- ▶ misspecified models are ok
 - ▶ flat model was wrong
 - ▶ flat model was best (lower variance)
- ▶ machine learning becomes a plug-in

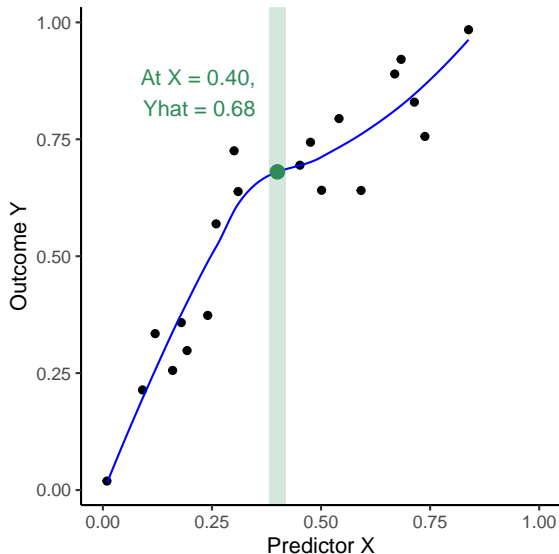
With \hat{Y} description,
machine learning becomes a plug-in

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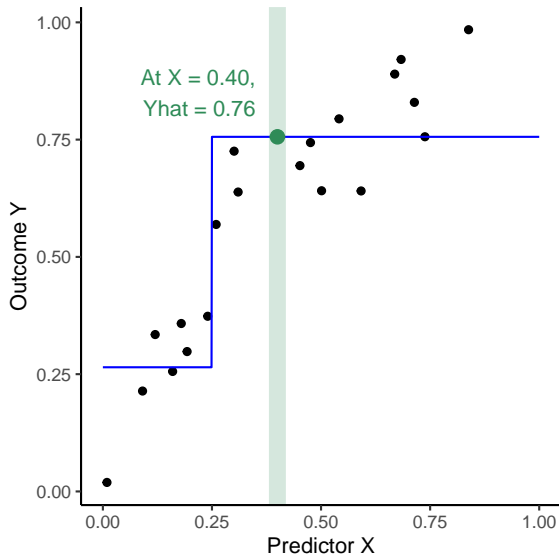
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With \hat{Y} description,
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Computer tutorial: Introduction

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Computer tutorial: Introduction

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We will give you data:

- ▶ male and female incomes at age 30–50 in 2010–2019

You will make a forecast:

- ▶ male and female geometric mean income at age 30–50 in 2022

Computer tutorial: Introduction

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Prepare the environment by loading the `tidyverse` package.

```
library(tidyverse)
```

The function below simulates a sample of 100 cases.

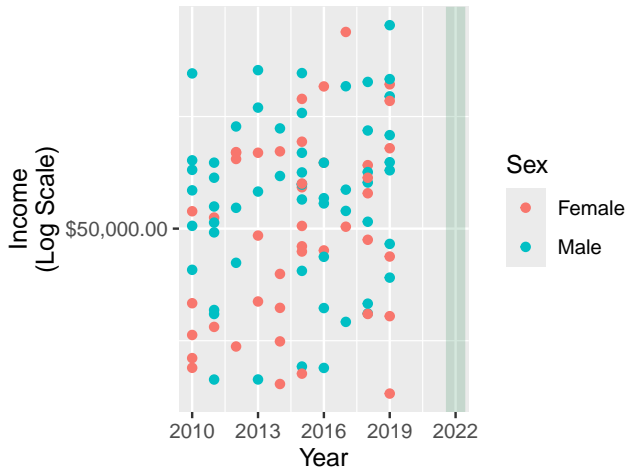
```
simulate <- function(n = 100) {  
  read_csv("https://ilundberg.github.io/description/assets/truth.csv") |>  
  slice_sample(n = n, weight_by = weight, replace = T) |>  
  mutate(income = exp(rnorm(n(), meanlog, sdlog))) |>  
  select(year, age, sex, income)  
}
```

We can see how it works below.

```
simulated <- simulate(n = 100)
```

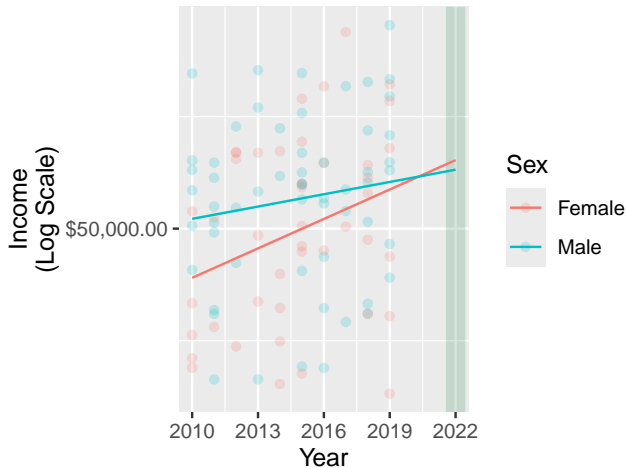
Computer tutorial: Introduction

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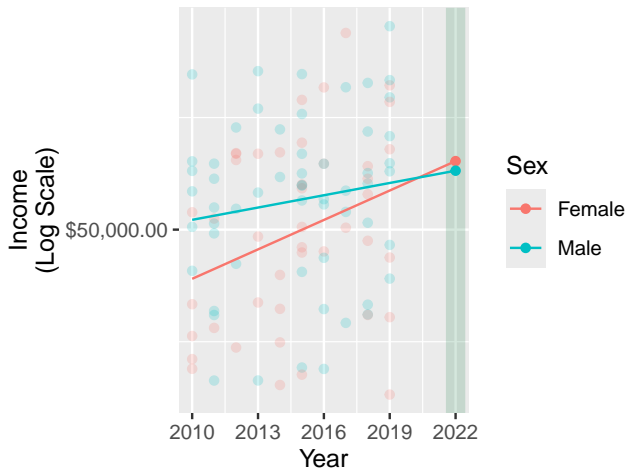
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Computer tutorial: Introduction

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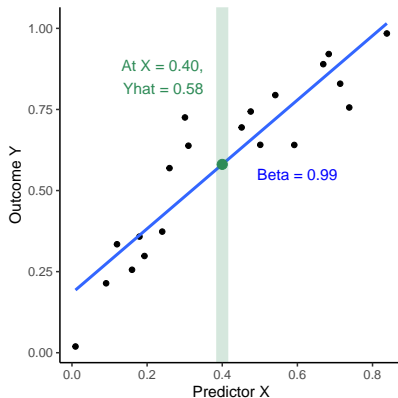
You will make a forecast:

- ▶ male and female geometric mean income at age 30–50 in 2022

We will see who comes closest

- ▶ to gold-standard truth from ACS 2022

Thanks!



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