

Engineering Patterns in Causal Inference

Jeffrey Wong, Airbnb
Antoine Creux, Airbnb

Causal Inference is a mathematically heavy field.

$$Y = \alpha + f(x)\beta_1 + g(A)\beta_2 + (f(x) \cdot g(A))\beta_3 + \varepsilon$$

$$ATE = E[Y|A = 1] - E[Y|A = 0]$$

$$\tau(x) = E[Y|A = 1, x] - E[Y|A = 0, x]$$

$$P(\text{good}) = Prob(\tau(x) \geq \epsilon)$$

A silver laptop is shown from a front-facing perspective, open. The screen is white and displays the text "What role does software play?" in a large, black, sans-serif font. The text is centered on the screen and arranged in two lines. The laptop's bezel and keyboard area are visible at the bottom and sides, and a small camera module is visible at the top center of the bezel.

What role does
software play?

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Causal reasoning is a principle of intelligent engineering systems.



Homes



NEW

Experiences







NEW

Services

Causal reasoning is a principle of intelligent engineering systems.



Causal reasoning is a principle of intelligent engineering systems.

	Business	Leisure
Arrived		
Not Arrived		

Software
solves for

1. Scalability
2. Multiplicity
3. Grammar

Scalability

Through Numerical Methods

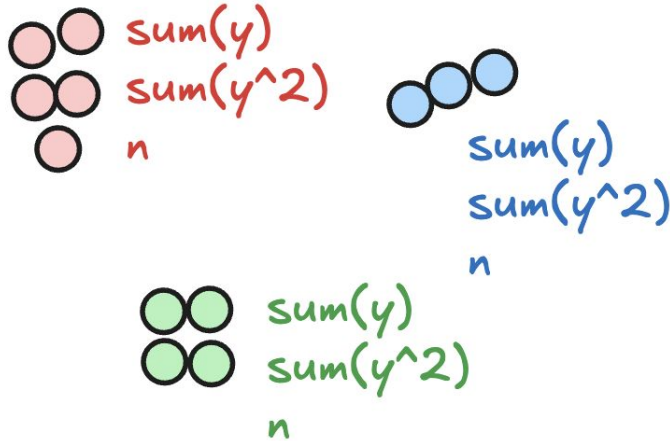
We need scalability at the speed of thought.



We need software that processes data and train models efficiently.

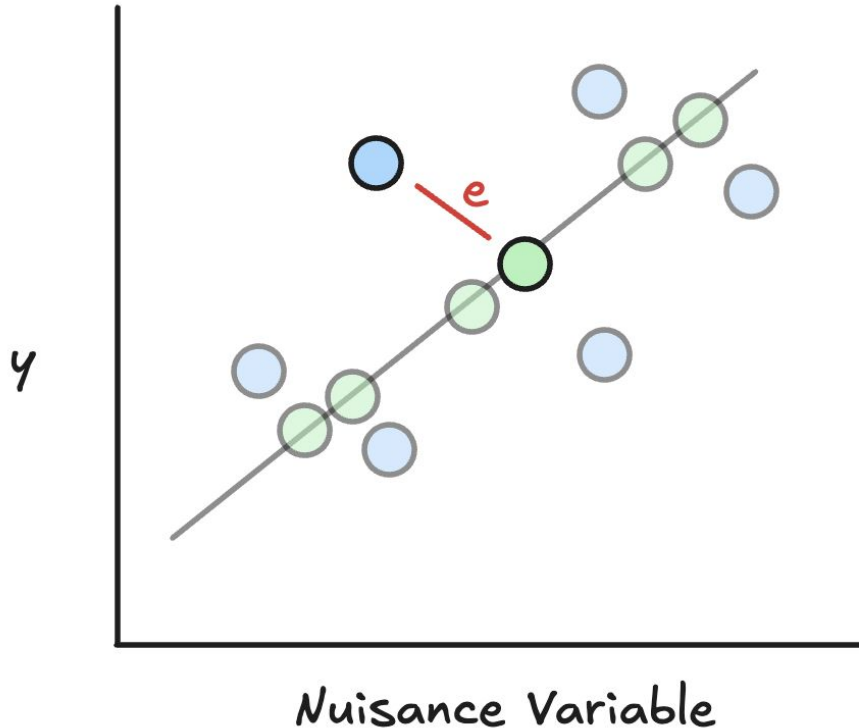


Sufficient Statistics lets you train on aggregates without bias.



$$\begin{aligned} RMSE &= \sum_i (y_i - \hat{y}_i)^2 \\ &= \sum_i (y_i^2 - 2\hat{y}_i y_i + \hat{y}_i^2) \\ &= \sum_g \sum_i (y_i^2) - \sum_g 2\hat{y}_g \sum_i y_i + \sum_g n_g \hat{y}_g^2 \end{aligned}$$

Increase efficiency by residualizing out nuisance variables.



$$y = f(T) + g(S) + h(T, S)$$

[Quasi Oracle Estimation Of HTE \(Nie and Wager\)](#)

Querying for Multiplicity

Multiple...

1. Metrics
2. Arms
3. Segments
4. Models

Multiplicity is layers and layers of loops.

```
for model in models:
    model.fit(metrics, arms, segments)
    for metric in metrics:
        for arm in arms:
            for segment in segments:
                y_treatment = model.predict(metric, arm, segment)
                y_control   = model.predict(metric, "control", segment)
                effect = mean(y_treatment) - mean(y_control)
```

Vectorization unrolls the loops.

```
for model in models:  
    model.fit(metrics, arms, segments).infer_effect(segments)
```

Vectorizing OLS

$$\hat{\beta} = (X^T X)^{-1} X^T y$$

$$\begin{bmatrix} \tau \\ s \end{bmatrix} = \begin{bmatrix} \vdots & \vdots & \vdots \end{bmatrix} \begin{bmatrix} Y1 & Y2 & Y3 \end{bmatrix}$$

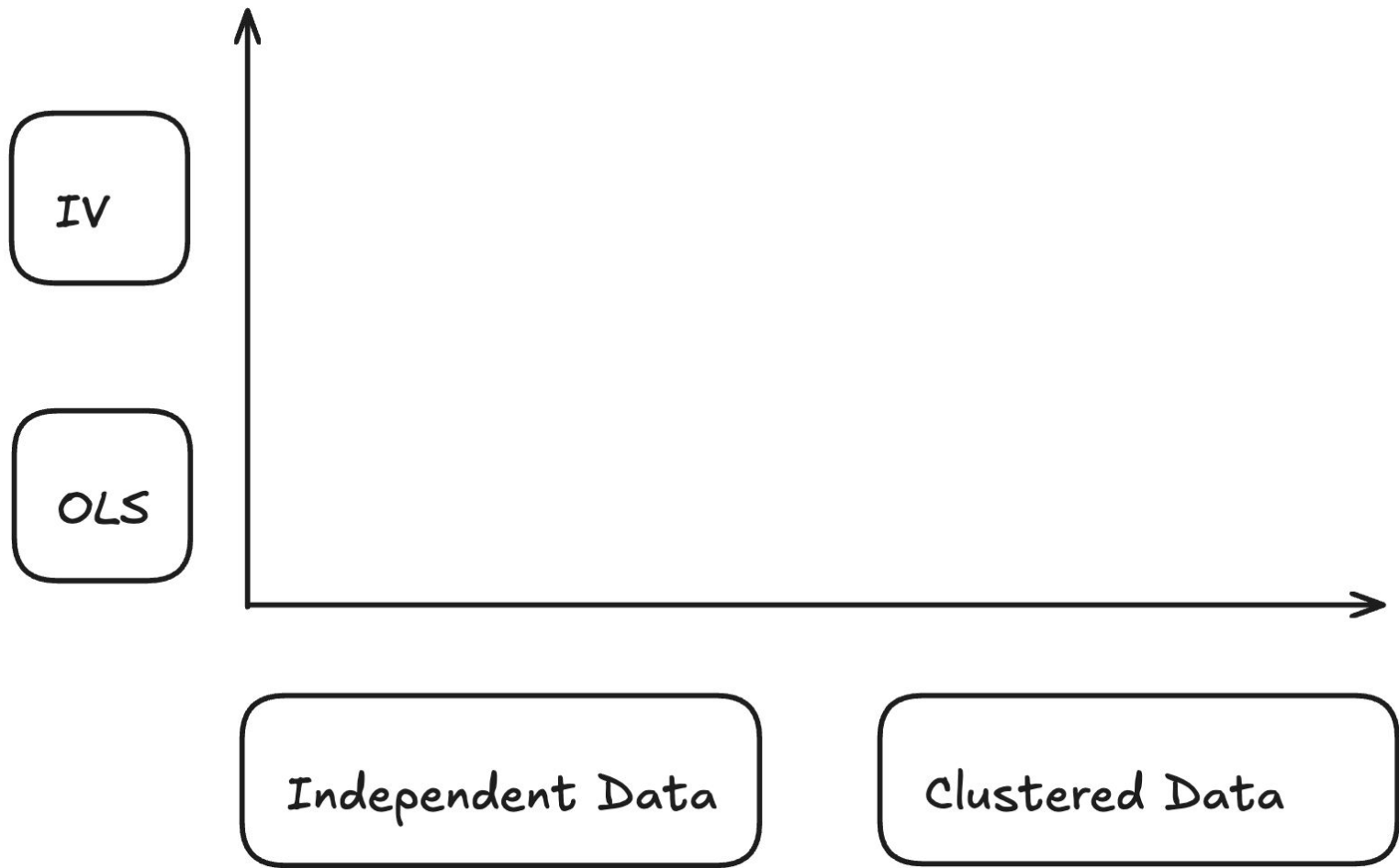
$$\tau(s) = \Delta(s) \hat{\beta}$$

Grammar

All causal
inquiries
have ...

1. Causal identification
2. Units
3. Features & metrics
4. Model parameters
5. Inference
6. External validity
7. Policy making & evaluation

```
Data(  
  treatment = "treatment",  
  instrument = "treatment",  
  unit_of_randomization = "host"  
)  
.add_metrics([  
  Revenue,  
  Engagement,  
  unit_of_analysis = "listing"  
])
```

```
.add_model(  
    OLS,  
    features = [...]  
)  
.aggregate()
```

```
.fit(  
    ~ treatment + <features>  
)  
.infer_effect(  
    condition_on = [  
        "country == 'US' "  
    ]  
)
```

```
Data(  
  treatment = "treatment",  
  instrument = "treatment",  
  unit_of_randomization = "host"  
)  
.add_metrics([  
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```

Key Takeaways

- Causal reasoning is a principle for intelligent engineering systems.
- We need engineers to think about scalable training for causal models
- Good causal software creates a stack for training models and querying models, and needs a grammar to solve for multiplicity.

If you'd like to develop
together, reach out!

jeffrey.wong@airbnb.com