# SAS® GLOBAL FORUM 2020

MARCH 29 – APRIL 1
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USERS PROGRAM

# Causal Effect Estimands: Interpretation, Identification, and Computation

**Reference:**

Thompson, C., Lamm, M., and Yung, Y.-F. (2019). “Causal Effect Estimands: Interpretation, Identification, and Computation.” In *Proceedings of the SAS Global Forum 2020 Conference*. Cary, NC: SAS Institute, Inc.

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**Causal Analysis in SAS/STAT 15.1:**

https://support.sas.com/rnd/app/stat/15.1/causal-analysis.pdf

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# Running Example

| Obs | ESL | PCGEd | ElmSize | MidSize | IncRatio | PreK | ElmProf | MidProf |
|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 4 | 19.6 | 26.3 | 3.3 | 0 | 1 | 1 |
| 2 | 0 | 5 | 19.2 | 26.1 | 4.7 | 1 | 0 | 1 |
| 3 | 0 | 4 | 18.7 | 26.1 | 3.3 | 1 | 0 | 1 |
| 4 | 1 | 4 | 17.1 | 23.4 | 3.3 | 0 | 1 | 1 |
| 5 | 0 | 2 | 17.5 | 24.5 | 2.2 | 0 | 0 | 1 |
| 6 | 0 | 3 | 17.6 | 23.8 | 0.4 | 0 | 0 | 1 |
| 7 | 0 | 3 | 19.5 | 26.0 | 0.3 | 1 | 1 | 1 |
| 8 | 0 | 2 | 19.2 | 26.4 | 3.4 | 1 | 0 | 1 |
| 9 | 0 | 5 | 19.7 | 27.0 | 4.1 | 1 | 1 | 1 |
| 10 | 0 | 1 | 20.4 | 27.3 | 0.8 | 0 | 0 | 1 |

“Does enrollment in a PreK program improve school performance in later years?”

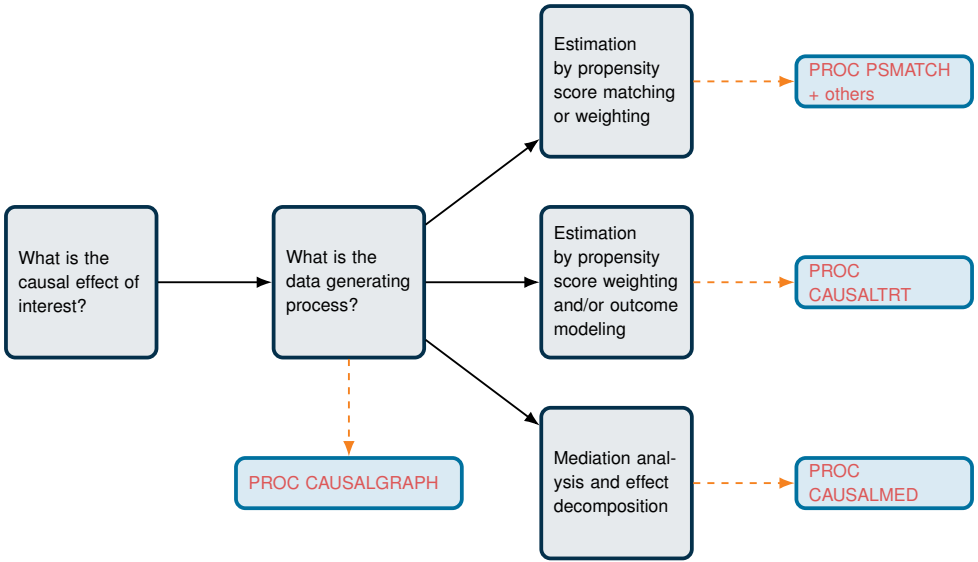
# Different research questions give rise to different causal estimands

- “What would be the effect of having every child enroll in PreK, compared to no child enrolled in PreK?”
  - Average Treatment Effect (ATE)
- “What is the effect of a PreK program among those children who were enrolled?”
  - Average Treatment Effect for the Treated (ATT)
- “What cost is incurred by students who are not enrolled in a PreK program?”
  - Average Treatment Effect for the Untreated (ATU)
- “How much of the total effect is (not) attributable to improved academic performance in early grades?”
  - Natural Indirect Effect (NIE), Natural Direct Effect (NDE)

# The SAS/STAT® product contains four procedures that are specifically designed for causal inference

| Procedure | Estimands | Primary Use | Release (Year) |
|---|---|---|---|
| PSMATCH | ATE, ATT, ATU | • Creation of matched data sets<br>• Assessing covariate balance in matched, weighted, or stratified data | SAS 9.4M4, SAS/STAT 14.2 (2016) |
| CAUSALTRT | ATE, ATT, ATU | • Direct estimation of a treatment effect | SAS 9.4M4, SAS/STAT 14.2 (2016) |
| CAUSALMED | ATE, NIE, NDE | • Causal mediation and related effects | SAS 9.4M5, SAS/STAT 14.3 (2017) |
| CAUSALGRAPH | Identification analysis | • Analysis of graphical causal models | SAS 9.4M6, SAS/STAT 15.1 (2018) |

# A simplified causal analysis workflow



# A well-considered workflow is essential to the clarity of your causal analysis

- Estimands in the Potential Outcomes Framework
  - Definitions and Assumptions
  - Causal Effect Estimands
- Using Data to Estimate Causal Effects
  - Randomization
  - Confounding
  - Identification
- Example: Estimating the Average Treatment Effect for the Treated
  - Identification Analysis with PROC CAUSALGRAPH
  - Effect Estimation with PROC PSMATCH
  - Effect Estimation with PROC CAUSALTRT
- Review of Key Themes

# Estimands in the Potential Outcomes Framework

# For simplicity, this presentation assumes a binary treatment variable

- **Treatment** $T$
  - Possible values $t$
  - Assume binary: $t \in \{0, 1\}$
- **Potential outcomes** $Y_t$
  - $Y_0$ and $Y_1$ for a binary treatment
  - Typically $Y_t = Y_t(Z)$, for some set of covariates $Z$

# Some assumptions are necessary in order to define the causal estimands

- **SUTVA**: the stable unit treatment value assumption
  - No hidden levels of treatment
  - No interference between subjects

- **Consistency**: $Y = Y_t$ if $T = t$
  - Treated: $T = 1 \Rightarrow Y = Y_1$
  - Untreated: $T = 0 \Rightarrow Y = Y_0$

# The SUTVA and consistency assumptions have practical implications

- No hidden levels of treatment
  - Are all PreK programs similarly effective?
  - Is the effect different for full-time vs. part time enrollment?
- No interference between subjects
  - To what extent are behaviors/norms collectivized?
  - Does this change with the density of enrollment?
- Consistent treatment assignment
  - Does the data reflect enrollment or attendance?

# Different research questions give rise to different causal estimands

(revisited)

- "What would be the effect of having every child enroll in PreK, compared to no child enrolled in PreK?"
  - Average Treatment Effect (ATE)
  - $\text{ATE} = \text{E}[Y_1 - Y_0] = \text{E}[Y_1] - \text{E}[Y_0]$
- "What is the effect of a PreK program among those children who were enrolled?"
  - Average Treatment Effect for the Treated (ATT)
  - $\text{ATT} = \text{E}[Y_1 - Y_0 \mid T = 1] = \text{E}[Y_1 \mid T = 1] - \text{E}[Y_0 \mid T = 1]$
- "What cost is incurred by students who are not enrolled in a PreK program?"
  - Average Treatment Effect for the Untreated (ATU)
  - $\text{ATU} = \text{E}[Y_1 - Y_0 \mid T = 0] = \text{E}[Y_1 \mid T = 0] - \text{E}[Y_0 \mid T = 0]$
- "How much of the total effect is (not) attributable to improved academic performance in early grades?"
  - Natural Indirect Effect (NIE), Natural Direct Effect (NDE)
  - $\text{NIE} = \text{E}[Y_{1M_1} - Y_{1M_0}] = \text{E}[Y_{1M_1}] - \text{E}[Y_{1M_0}]$
  - $\text{NDE} = \text{E}[Y_{1M_0} - Y_{0M_0}] = \text{E}[Y_{1M_0}] - \text{E}[Y_{0M_0}]$

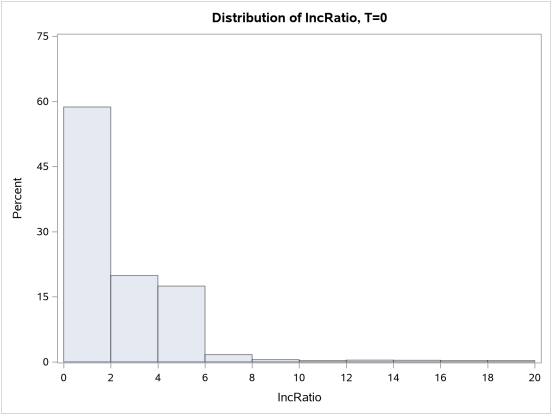
# The observed outcome is determined by the treatment received

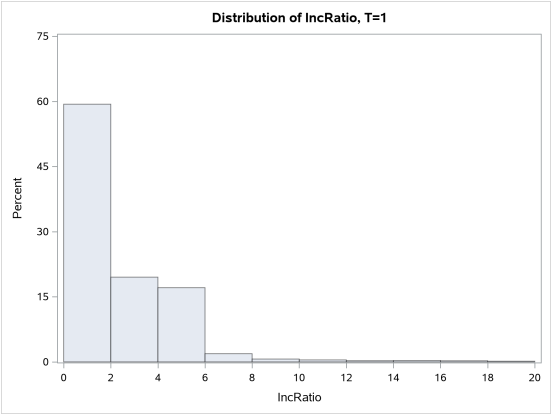
| Obs | $T$ | IncRatio | PCGEd | ESL | $Y_1$ | $Y_0$ | $Y$ |
|---|---|---|---|---|---|---|---|
| 1 | 0 | 3.3 | 4 | 0 | ? | 1 | 1 |
| 2 | 1 | 4.7 | 5 | 0 | 1 | ? | 1 |
| 3 | 1 | 3.3 | 4 | 0 | 0 | ? | 0 |
| 4 | 0 | 3.3 | 4 | 1 | ? | 1 | 1 |
| 5 | 1 | 2.2 | 2 | 0 | 1 | ? | 1 |
| 6 | 0 | 0.4 | 3 | 0 | ? | 0 | 0 |
| 7 | 0 | 0.3 | 1 | 0 | ? | 1 | 1 |
| 8 | 1 | 3.4 | 5 | 0 | 1 | ? | 1 |

- Consistency implies $Y = Y_t$ if $T = t$
  - Half of the potential outcomes are missing
  - "Causal inference is a missing data problem"
- How do you estimate a causal effect?
  - **Identification**: use observed data to construct an estimator

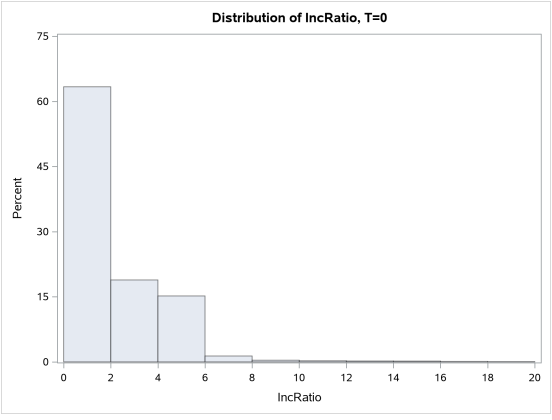
# Using Data to Estimate Causal Effects

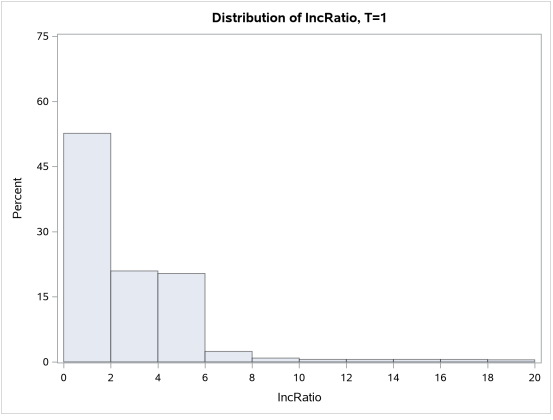
# Randomization creates groups that are exchangeable (on average)



# In observational studies, groups are no longer exchangeable



# Identification conditions are required for valid causal effect estimation

- **SUTVA**: the stable unit treatment value assumption
  - No hidden levels of treatment
  - No interference between subjects
- **Consistency**: $Y = Y_t$ if $T = t$
- **Positivity**: $P(T = t \mid \boldsymbol{X} = \boldsymbol{x}) > 0 \; \forall \; t, x$
- **Conditional Exchangeability**: $T \perp\!\!\!\perp Y_t \mid \boldsymbol{X}$

Conditional on $\boldsymbol{X} = \boldsymbol{x}$,
subjects are “as if randomized”

(**Conditional Ignorability**: Conditional Exchangeability + Positivity)

# Example: Estimating the Average Treatment Effect for the Treated

# What is the effect of a PreK program among those children who were enrolled?

| Obs | ESL | PCGEd | ElmSize | MidSize | IncRatio | PreK | ElmProf | MidProf |
|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 4 | 19.6 | 26.3 | 3.3 | 0 | 1 | 1 |
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| 10 | 0 | 1 | 20.4 | 27.3 | 0.8 | 0 | 0 | 1 |

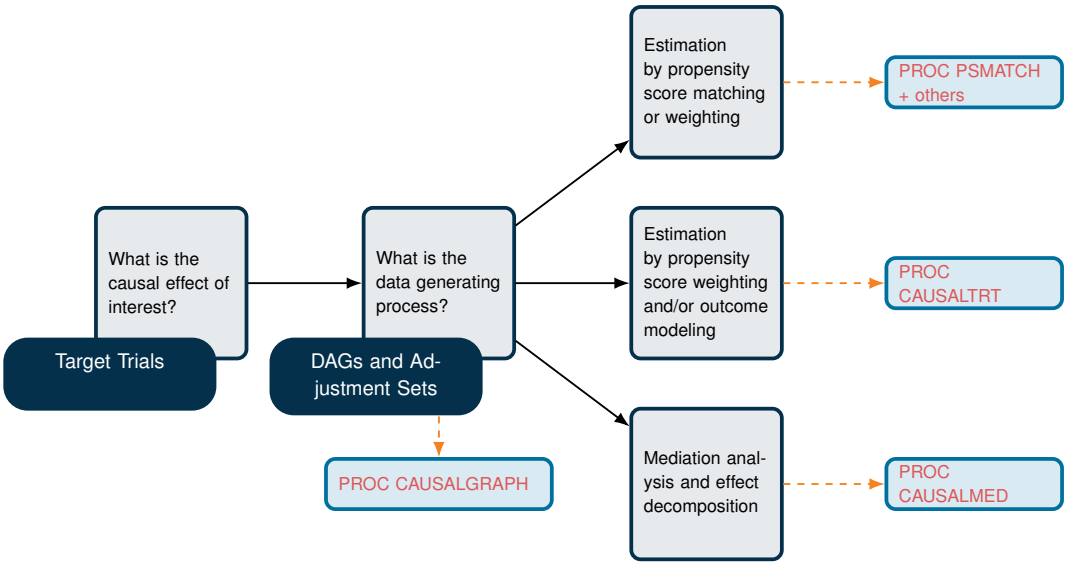
ATT = 0.0356

# This research question is answered by the ATT

- $\text{ATT} = \text{E}[Y_1 - Y_0 \mid T = 1] = \text{E}[Y_1 \mid T = 1] - \text{E}[Y_0 \mid T = 1]$
  - Subpopulation effect (those who enroll)
  - Useful to evaluate a pilot program

- Is the ATT identified by the available data?
  - SUTVA
  - Consistency
  - Conditional Ignorability

# Target trials and DAGs are useful to assess causal assumptions



# A “target trial” is a useful framework for creating well-defined causal questions

“Does enrollment in a PreK program improve school performance in later years?”

- Who will be studied?
  - What are the inclusion criteria?
  - What are the exclusion criteria?
- What intervention will be considered?
  - Will the exposure be similar for all treated subjects?
  - Is there a clear distinction between treated and untreated subjects?
- What are the study endpoints?
  - When will they be collected?
  - How do they relate to the outcome?

# The refined causal question is more likely to satisfy SUTVA and consistency

"Does full-time enrollment in a specific PreK program improve reading performance as measured by a standardized assessment of reading proficiency at the end of eighth grade?"

For more information about target trials, see Hernán and Robins (2016).

# Which set(s) of covariates satisfy the conditional ignorability assumption?

Conditional ignorability: $Y_t \perp\!\!\!\perp T | \boldsymbol{X}$

| Obs | ESL | PCGEd | ElmSize | MidSize | IncRatio | PreK | ElmProf | MidProf |
|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 4 | 19.6 | 26.3 | 3.3 | 0 | 1 | 1 |
| 2 | 0 | 5 | 19.2 | 26.1 | 4.7 | 1 | 0 | 1 |
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| 9 | 0 | 5 | 19.7 | 27.0 | 4.1 | 1 | 1 | 1 |
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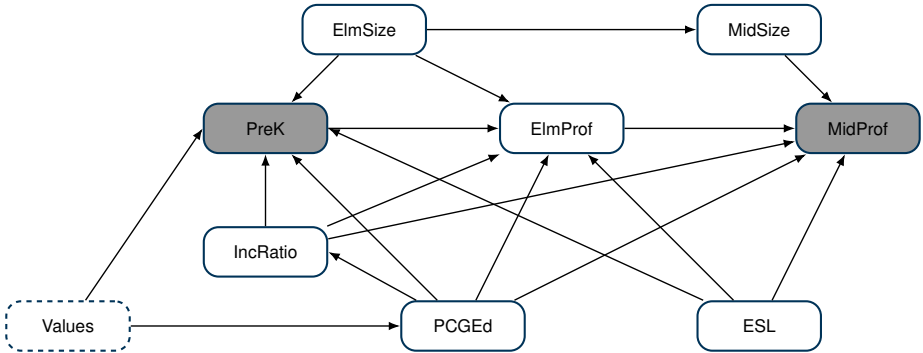
# A causal graph represents assumptions about the data generating process




For more information about using expert judgment to form a causal diagram, see Hanea et al. (2018).

# Use PROC CAUSALGRAPH to find valid adjustment sets

```
proc causalgraph;
   model "ReadingProf"
      ElmProf => MidProf, MidSize => MidProf,
      ElmSize => ElmProf MidSize PreK,
      ESL IncRatio => ElmProf MidProf PreK,
      PCGEd => ElmProf IncRatio MidProf PreK,
      PreK => ElmProf, Values => PCGEd PreK;
   latent Values;
   identify PreK => MidProf;
run;
```

# Each valid adjustment set represents a possible identification strategy

| Covariate Adjustment Sets for ReadingProf | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Causal Effect of PreK on MidProf | | | | | | | | |
| | | | Covariates | | | | | |
| | Size | Minimal | ElmProf | ElmSize | ESL | IncRatio | MidSize | PCGEd |
| 1 | 4 | Yes | | * | * | * | | * |
| 2 | 5 | No | | * | * | * | * | * |

A valid adjustment set satisfies $T \perp\!\!\!\perp Y_t \mid \boldsymbol{X}$

For more information about PROC CAUSALGRAPH, see Thompson (2019).

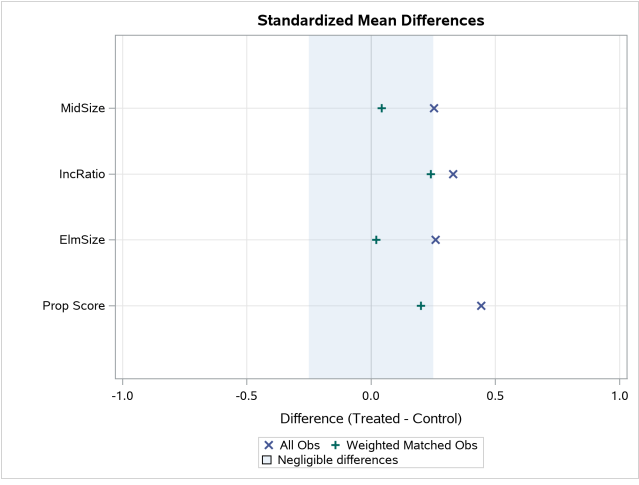
# You can use PROC PSMATCH to produce a matching analysis

```
proc psmatch data=ReadingObs region=treated;
   class ESL PCGEd PreK;
   psmodel PreK(treated="1") = ElmSize ESL IncRatio PCGEd;
   match method = optimal caliper=.;
   assess ps var=(ElmSize IncRatio MidSize) /
          plots(nodetails)=(stddiff box(display=(PS IncRatio)));
   output out=psATTMatchData weight=attWgt;
run;
```

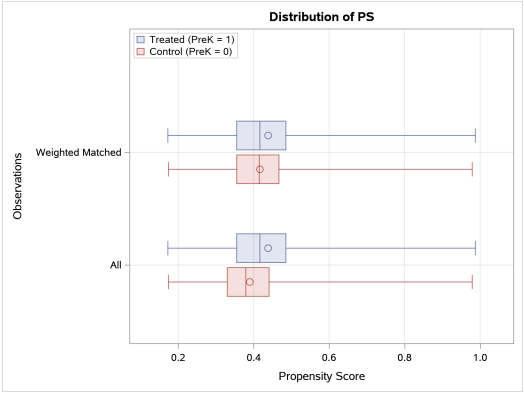
For more information about PROC PSMATCH, see:

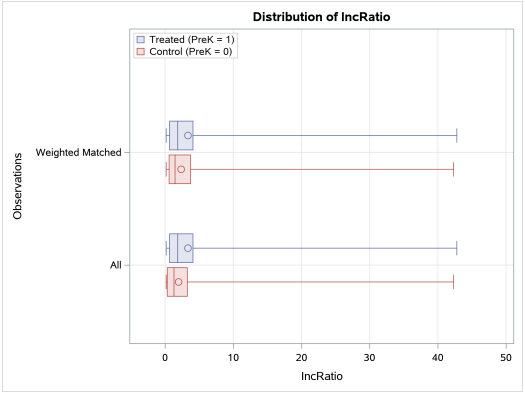
- Yuan, Yung, and Stokes (2017)
- Lamm, Thompson, and Yung (2019)

# Standardized mean differences diagnostics show a modest improvement in balance after matching

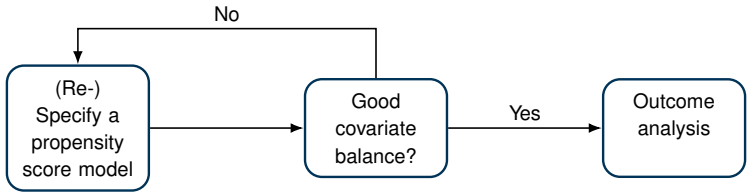


# Covariate balance diagnostics also show modest improvement



# Matching is an iterative process that excludes the outcome variable



# Use the PSMATCH output data set to estimate the causal effect

```
proc ttest data=psATTMatchData;
   class PreK;
   var MidProf;
   weight attWgt;
run;
```

| PreK | Method | Mean | 95% CL Mean | | Std Dev | 95% CL Std Dev | |
|---|---|---|---|---|---|---|---|
| 0 | | 0.7574 | 0.7443 | 0.7706 | 0.4287 | 0.4196 | 0.4382 |
| 1 | | 0.7987 | 0.7864 | 0.8110 | 0.4010 | 0.3925 | 0.4099 |
| Diff (1-2) | Pooled | -0.0412 | -0.0592 | -0.0233 | 0.4151 | 0.4088 | 0.4215 |
| Diff (1-2) | Satterthwaite | -0.0412 | -0.0592 | -0.0233 | | | |

# You can use CAUSALTRT to estimate the ATT by inverse probability weighting

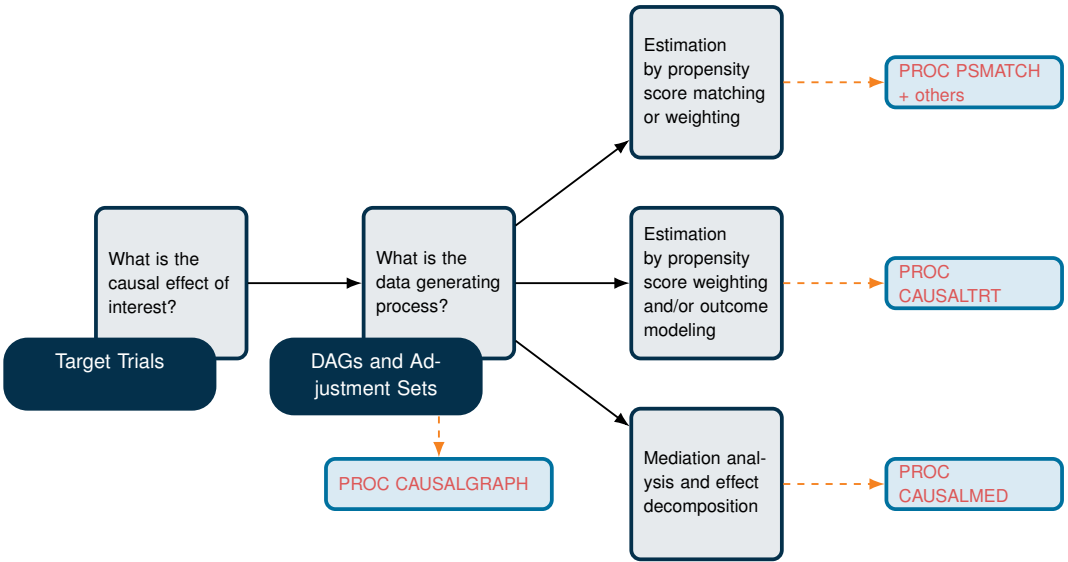
```
proc causaltrt data=ReadingObs att;
   class ESL MidProf PCGEd PreK / desc;
   psmodel PreK = ElmSize ESL IncRatio PCGEd;
   model MidProf;
   bootstrap seed=1976;
run;
```

**Analysis of Causal Effect**

| Parameter | Treatment Level | Estimate | Robust Std Err | Bootstrap Std Err | Wald 95% Confidence Limits | | Bootstrap Bias Corrected 95% Confidence Limits | | Z | Pr > \|Z\| |
|---|---|---|---|---|---|---|---|---|---|---|
| POM | 1 | 0.7987 | 0.00626 | 0.00611 | 0.7864 | 0.8110 | 0.7862 | 0.8106 | 127.51 | <.0001 |
| POM | 0 | 0.7644 | 0.00636 | 0.00643 | 0.7519 | 0.7768 | 0.7517 | 0.7774 | 120.26 | <.0001 |
| ATT | | 0.03430 | 0.00883 | 0.00889 | 0.01700 | 0.05160 | 0.01540 | 0.05075 | 3.89 | 0.0001 |

# Review of Key Themes

# Target trials and DAGs are useful to assess causal assumptions



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# References I


Hanea, A. M., McBride, M. F., Burgman, M. A., and Wintle, B. C. (2018). "Classical Meets Modern in the IDEA Protocol for Structured Expert Judgement." *Journal of Risk Research* 21:417–433.

Hernán, M. A., and Robins, J. M. (2016). "Using Big Data to Emulate a Target Trial When a Randomized Trial Is Not Available." *American Journal of Epidemiology* 183:758–764.

Lamm, M., Thompson, W. C., and Yung, Y.-F. (2019). "Building a Propensity Score Model with SAS/STAT Software: Planning and Practice." In *Proceedings of the SAS Global Forum 2019 Conference*. Cary, NC: SAS Institute Inc. `https://www.sas.com/content/dam/SAS/support/en/sas-global-forum-proceedings/2019/3056-2019.pdf`.

Thompson, W. C. (2019). "Causal Graph Analysis with the CAUSALGRAPH Procedure." In *Proceedings of the SAS Global Forum 2019 Conference*. Cary, NC: SAS Institute Inc. `https://www.sas.com/content/dam/SAS/support/en/sas-global-forum-proceedings/2019/2998-2019.pdf`.

# References II

Yuan, Y., Yung, Y.-F., and Stokes, M. (2017). “Propensity Score Methods for Causal Inference with the PSMATCH Procedure.” In *Proceedings of the SAS Global Forum 2017 Conference*. Cary, NC: SAS Institute Inc. `http://support.sas.com/resources/papers/proceedings17/SAS0332-2017.pdf`.

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# PROC CAUSALGRAPH can be used to find valid adjustment sets

- List valid identification strategies or test a user-specified strategy
- Multiple identification criteria:
  - Constructive backdoor criterion
  - Backdoor criterion
  - Conditional instrumental variable criterion
- Specify unmeasured, latent, or excluded variables
- Explore causal and noncausal paths between treatments and outcomes
- Enumerate observationally testable assumptions in a model
- Analyze multiple models simultaneously
- Analyze any static treatment regime (multiple treatments, multiple outcomes)

# PROC PSMATCH can build propensity score models for weighting or matching

- Create propensity scores by fitting a logistic regression model
- Input propensity scores created by some other method
- Compute ATE or ATT weights
- Multiple matching strategies, including caliper restrictions
  - Greedy nearest neighbor
  - Optimal matching (fixed ratio, variable ratio, full)
  - Matching with replacement
- Many tabular and graphical assessments of covariate balance

# PROC CAUSALTRT can estimate total causal effects directly

- Same theoretical foundation and similar functionality to PSMATCH
- Create propensity scores by fitting a logistic regression model
- Use computed propensity scores to estimate causal effects directly
- Supports outcome regression to estimate causal effects
- Supports doubly robust estimation

# PROC CAUSALMED can perform a causal mediation analysis

- Maximum likelihood estimation of causal mediation effects by regression adjustment methods
- Bootstrap and asymptotic estimation of standard errors and confidence intervals
- Support of various data types:
  - continuous or binary outcome, treatment, and mediator variables
  - continuous or categorical covariates
- Several two-, three-, and four-way decompositions of total effects
- Flexible evaluation of controlled direct effects and conditional mediation effects
- Analysis with case-control design