Learning Models from Data with Measurement Error: Tackling Underreporting

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Introduction

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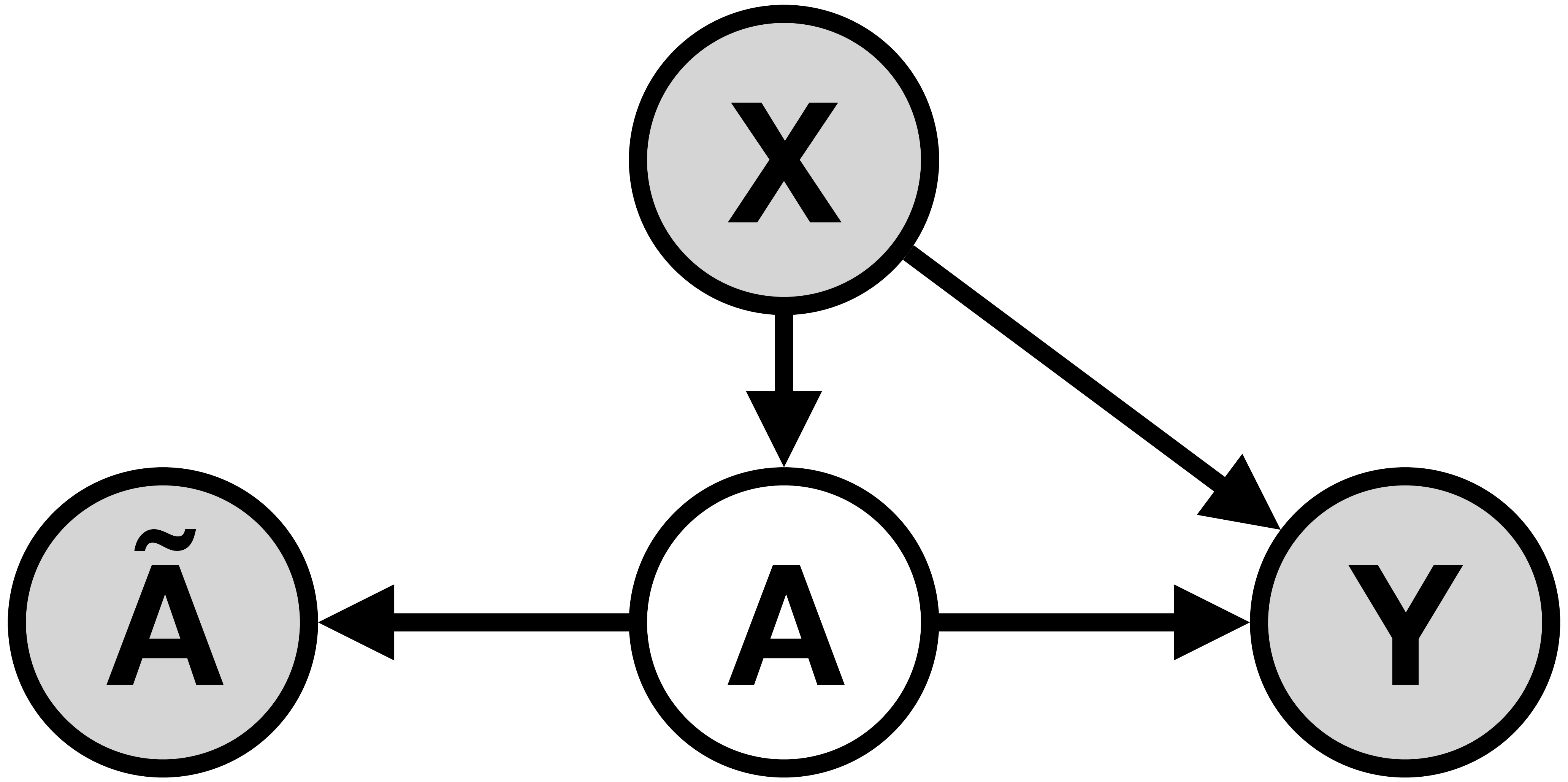
- We focus on **underreporting error.**
  - E.g. survey data of sensitive variables such as drug use.

Model

Updated goal: Estimate the distribution of outcome Y given exposure A and covariates X when **exposure observations Ã are subject to underreporting errors**.



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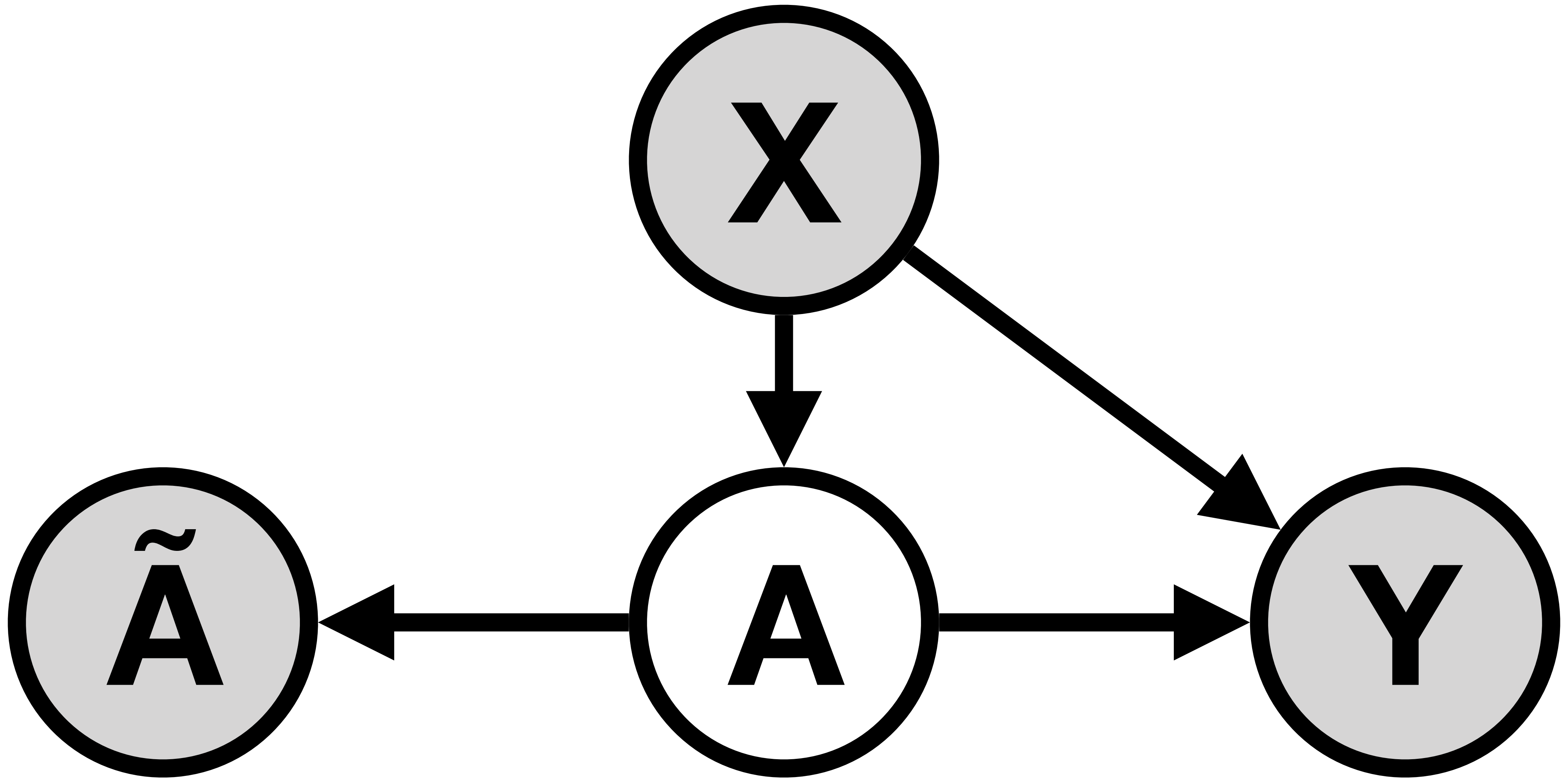
Assumptions:



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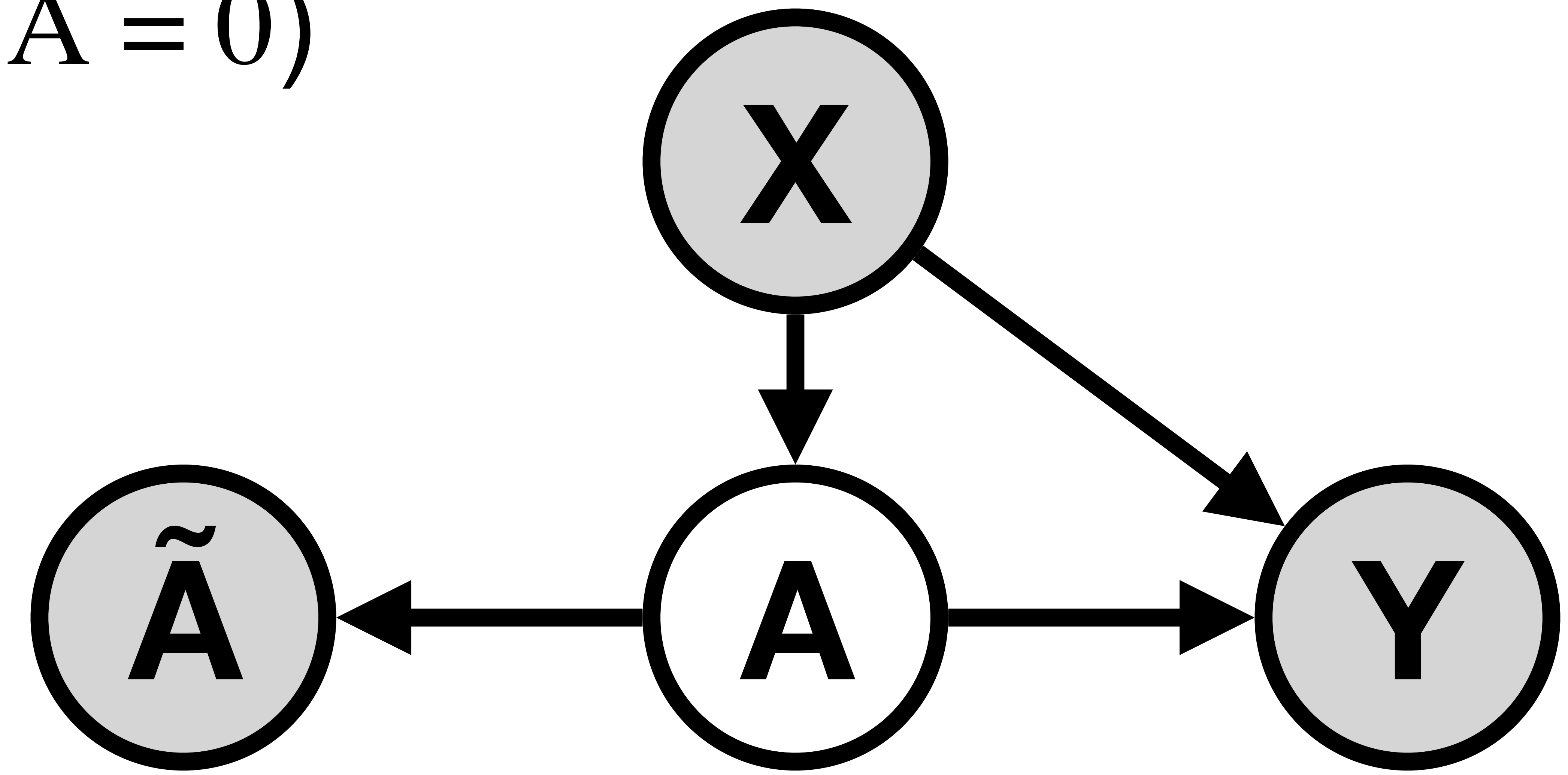
1. Strict underreporting ($A = 0 \implies \tilde{A} = 0$)



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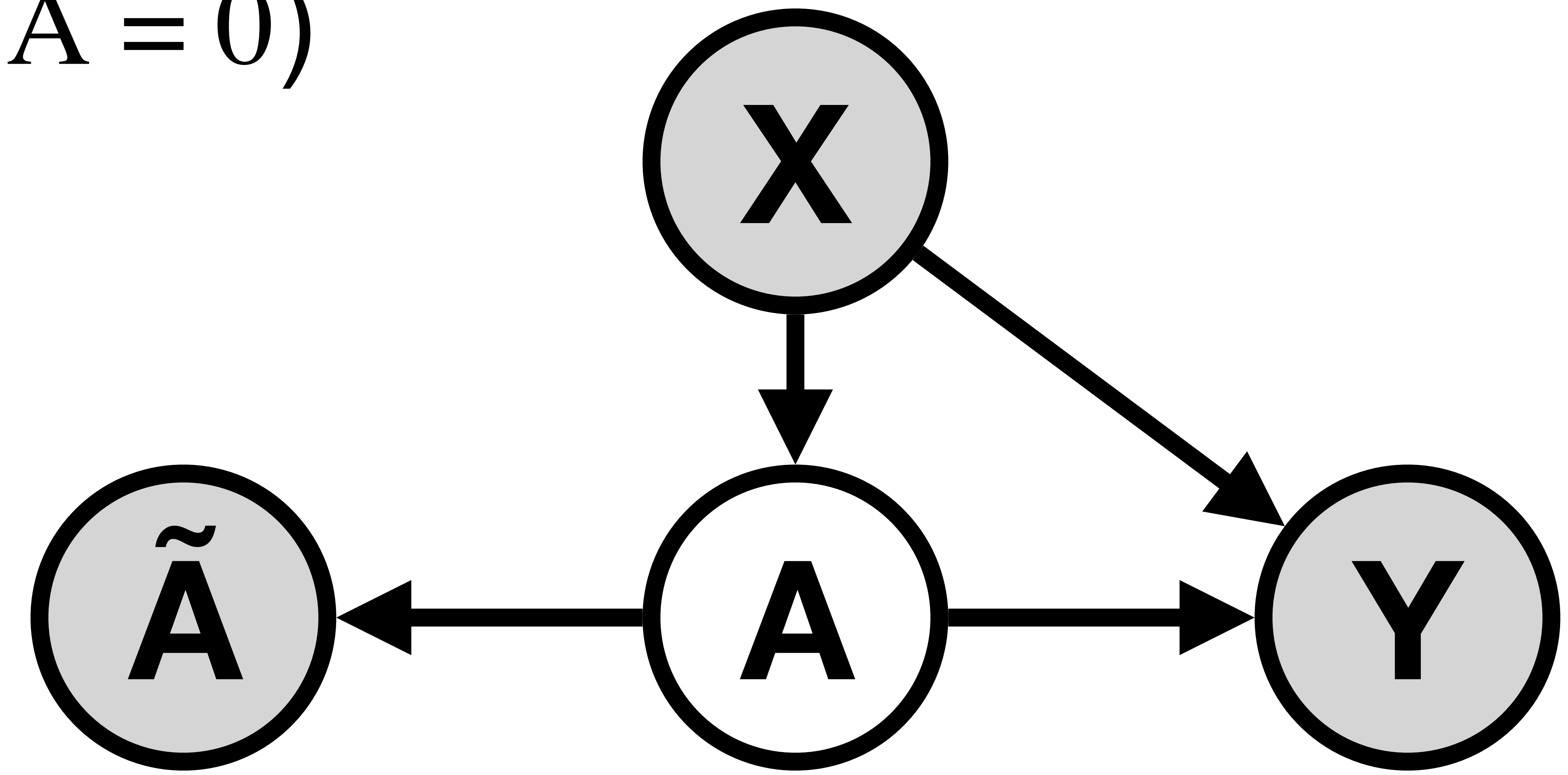
Assumptions:

1. Strict underreporting ($A = 0 \implies \tilde{A} = 0$)
2. $\tilde{A}$ is independent of X given A



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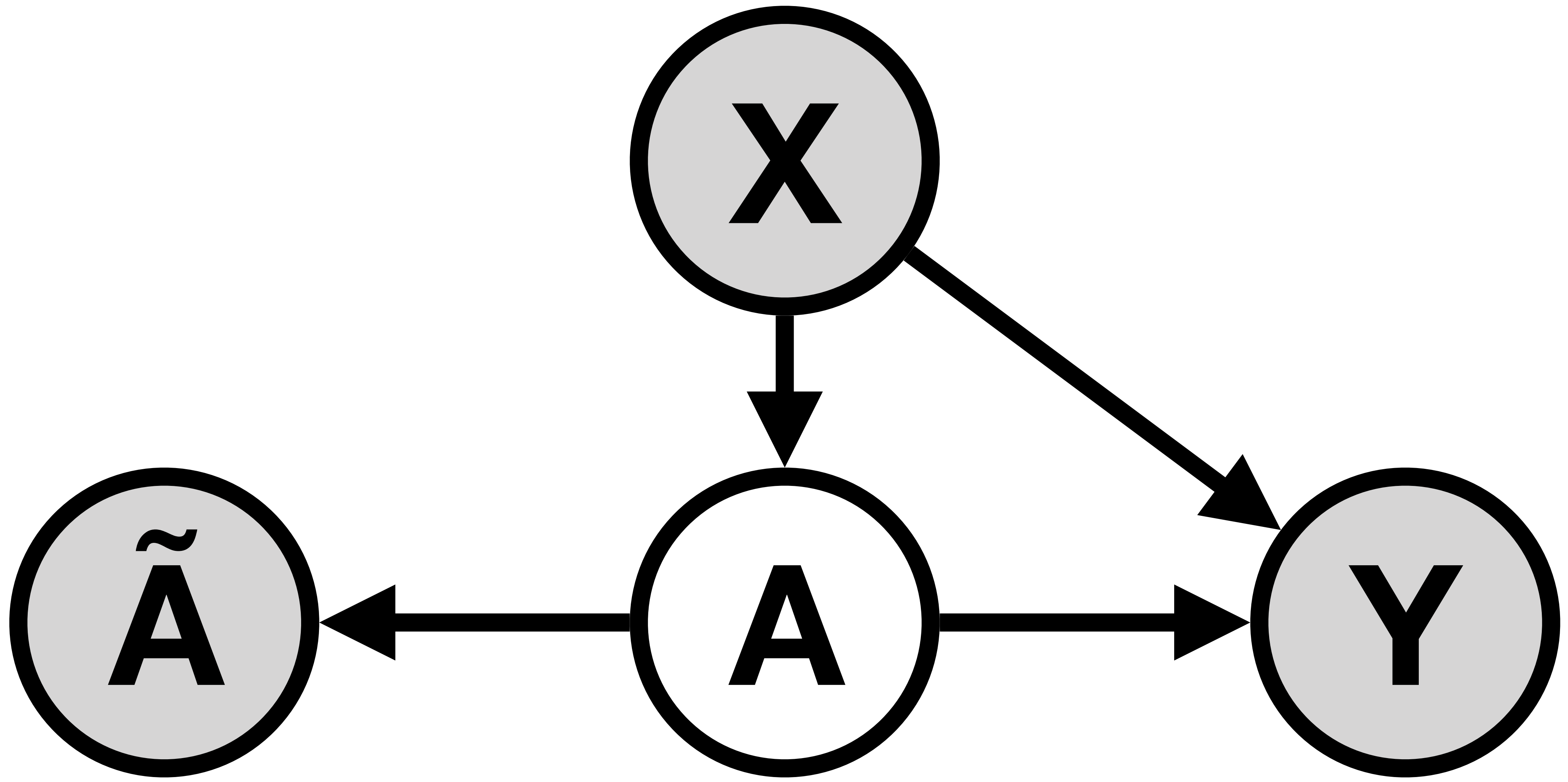
Outcome model … $p_\theta(Y \mid A, X)$

Exposure model … $p_\phi(A \mid X)$

Error model ……… $p_\tau(\tilde{A} \mid A)$



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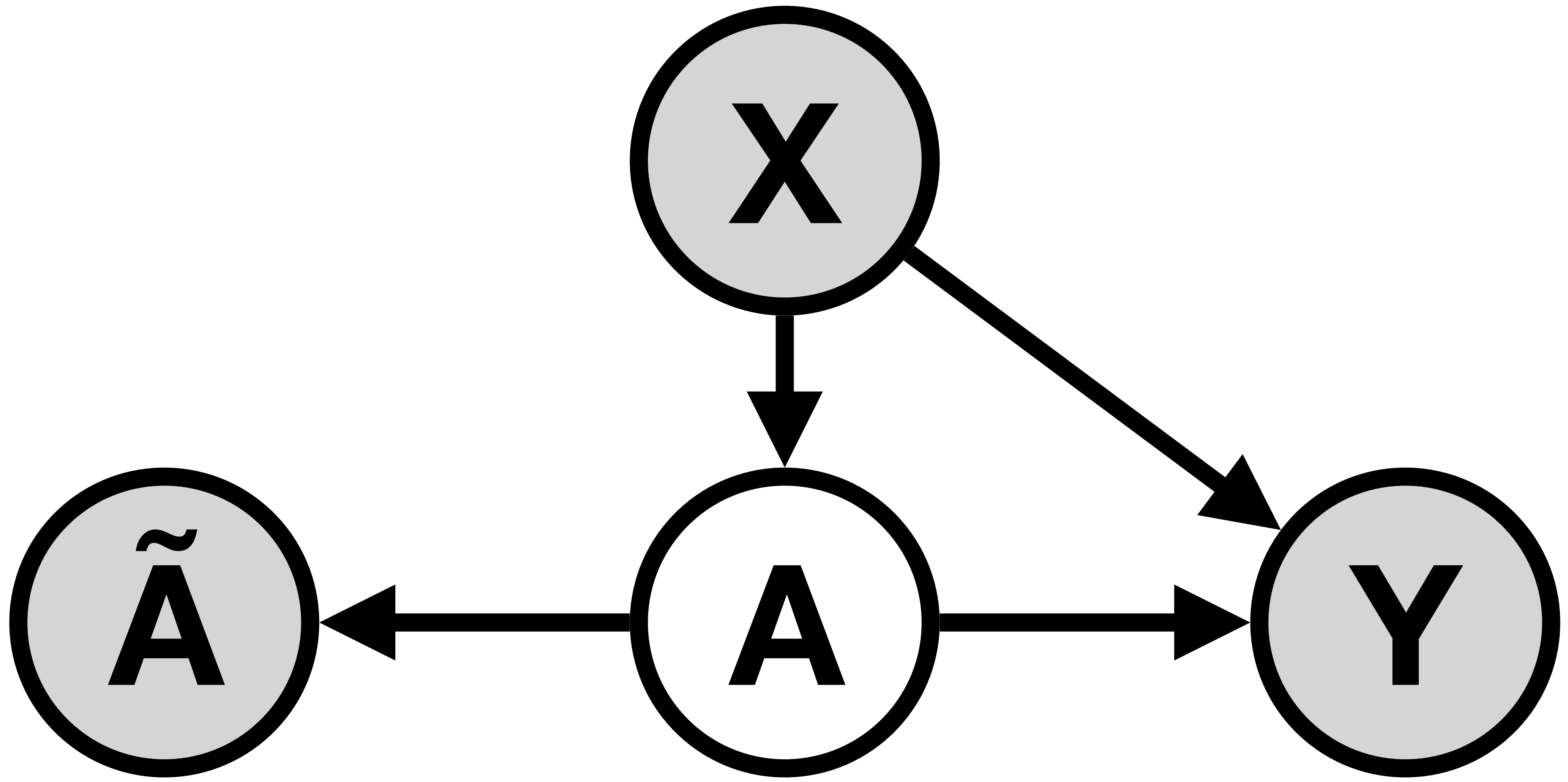

Maximize the **log marginal likelihood**:

$$\max_{\theta,\phi,\tau} \sum_i \log \sum_a p_\theta(y_i \mid a, x_i) p_\tau(\tilde{a}_i \mid a) p_\phi(a \mid x_i)$$

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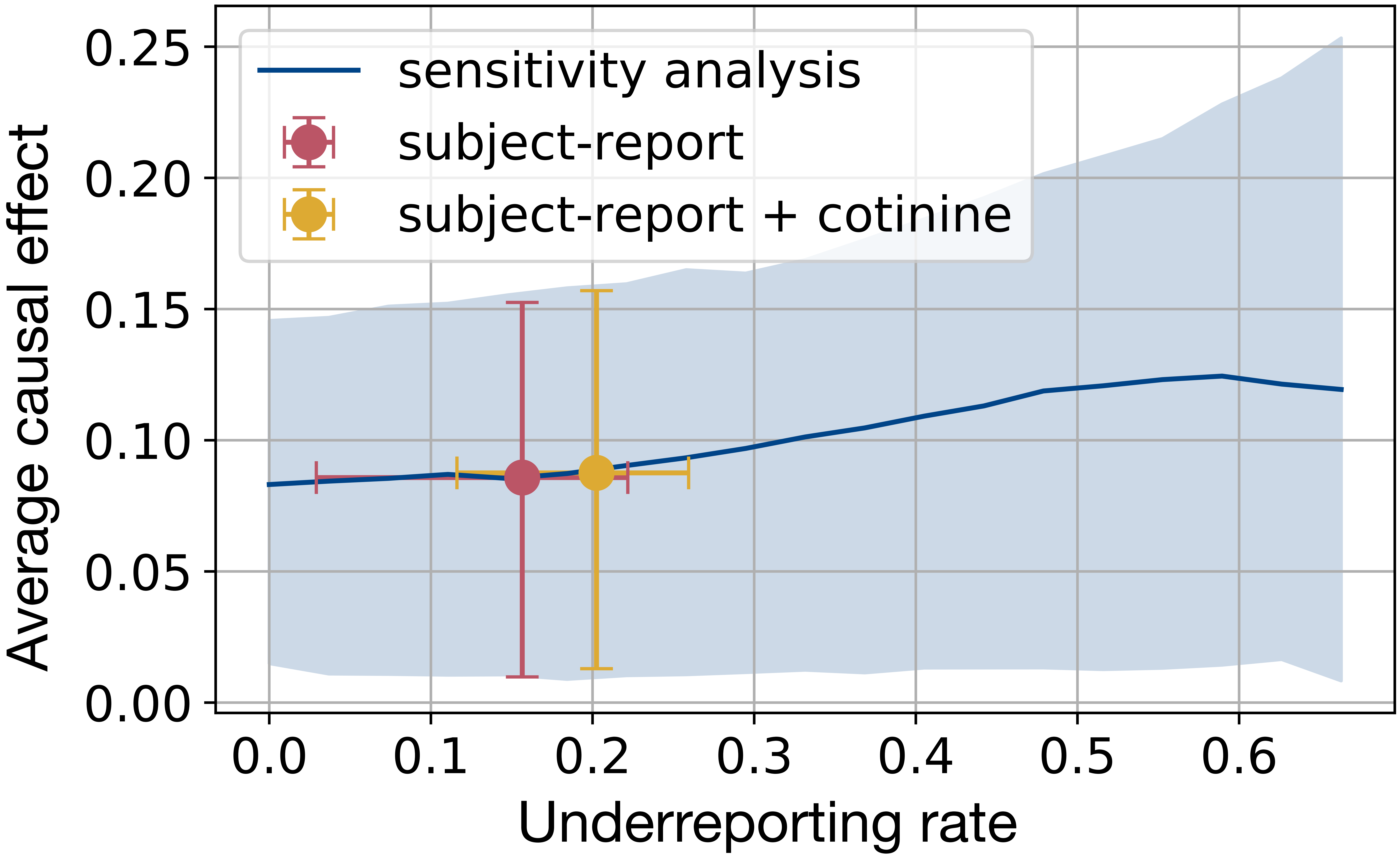
In particular:

If $\mathbf{X}$ **is not independent of** $\mathbf{A}$ and $p(A \mid X)$ is a **logit, probit, or cloglog regression model**, then $p(Y, \tilde{A} \mid X)$ is identifiable.

Maternal drug use and childhood obesity



Thanks!

Come see poster #75