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Learning Causal Effects via Weighted Empirical Risk Minimization

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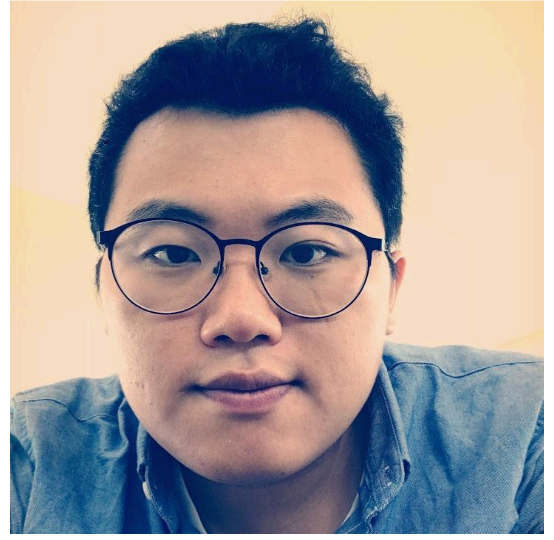

Learning causal effect: 2-step procedures

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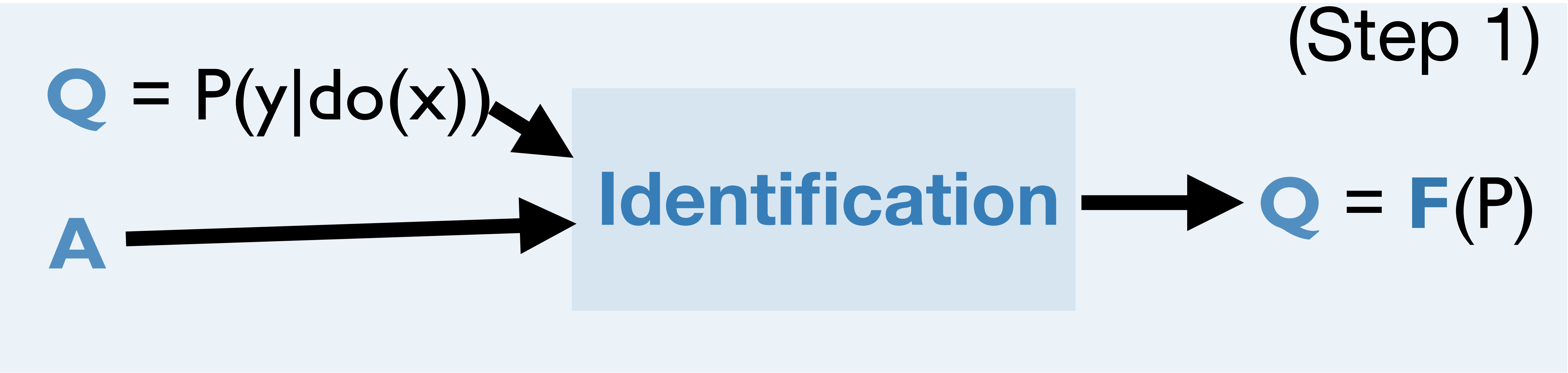
Step 1.
(Identification)

Represent the causal query Q=P(y|do(x)) as a function of P (i.e., Q=F(P)) from causal assumption A.



Learning causal effect: 2-step procedures

Step 1. (Identification)

Represent the causal query Q=P(y|do(x)) as a function of P (i.e., Q=F(P)) from causal assumption A.

Step 2. (Estimation)

Estimate the identified estimand Q=F(P) from finite samples D

Current status of causal inference

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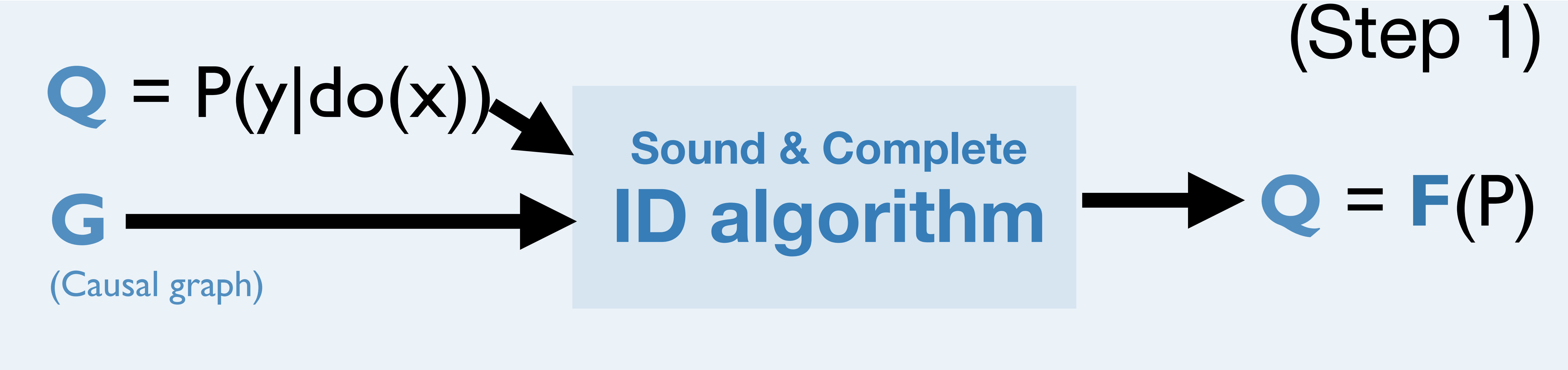
Strength

- We have a sound and complete identification algorithm — A procedure for determining whether a causal query Q is could be represented as a functional of P (i.e., Q=F(P)) from the causal assumption.



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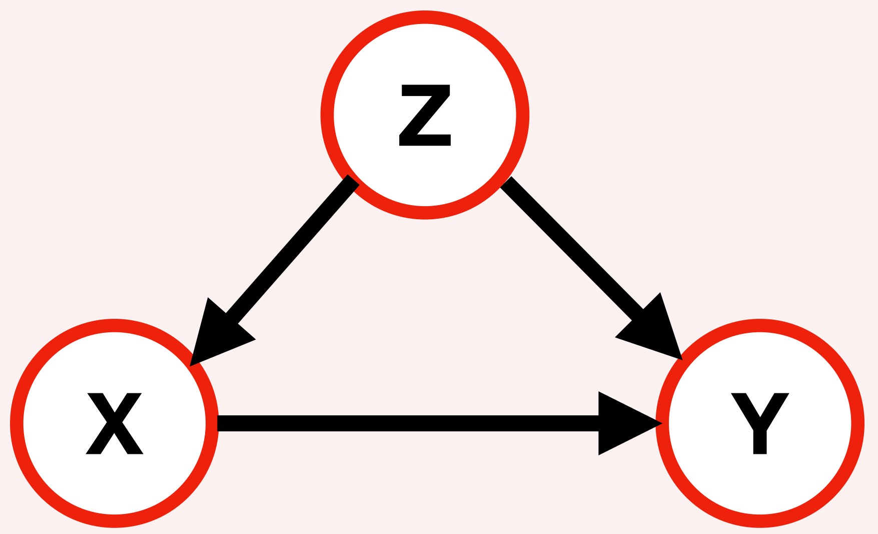

Ignorability assumption

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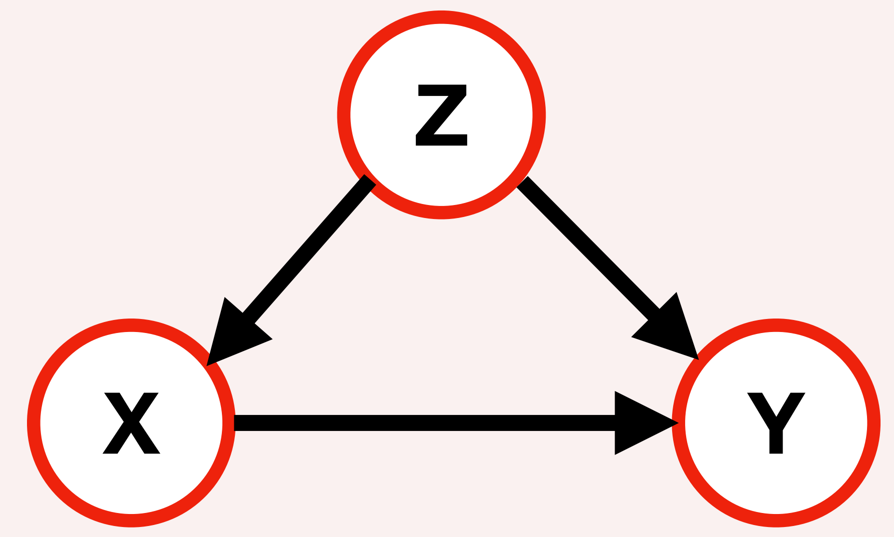

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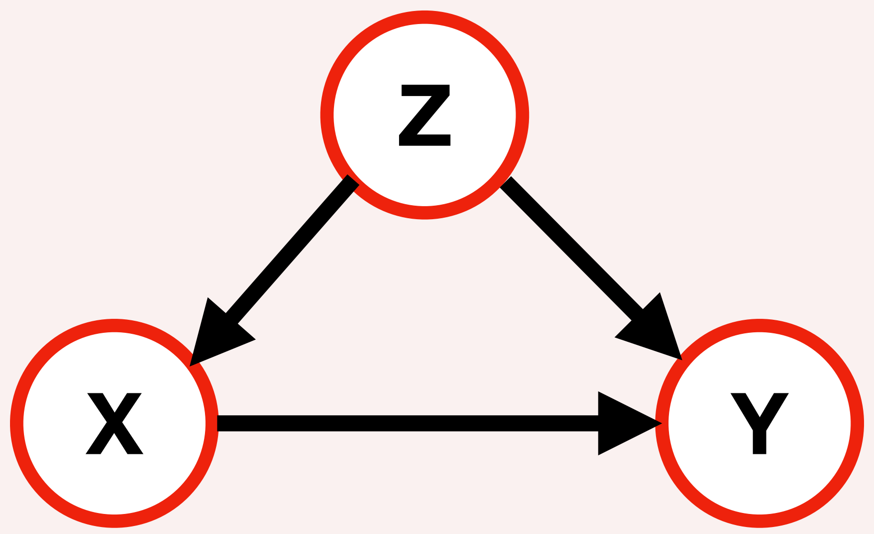

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- When Q=F(P) is given as ***weighed distribution*** (e.g., *inverse probability weights (IPW) or importance sampling)*, then the empirical risk minimization (ERM) based estimators have been established.

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Swaminathan and Joachims (2015)
Re-weighted Risk Minimization
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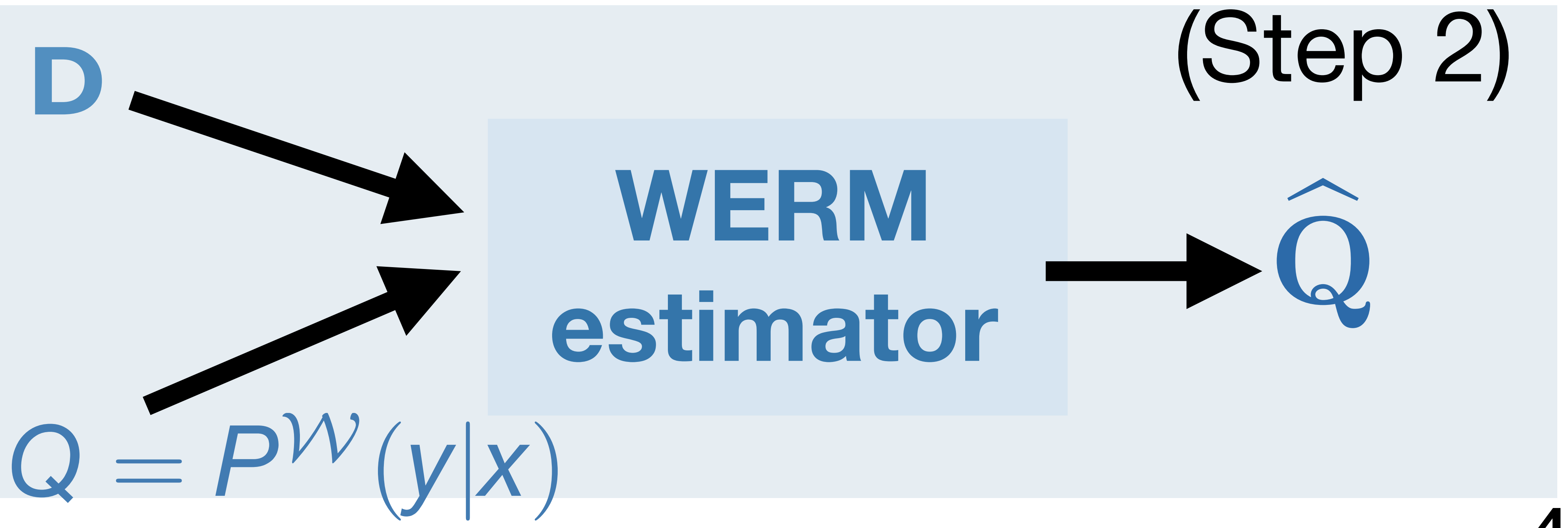

(e.g., W=P(x)/P(x|z) under ignorability assumption)

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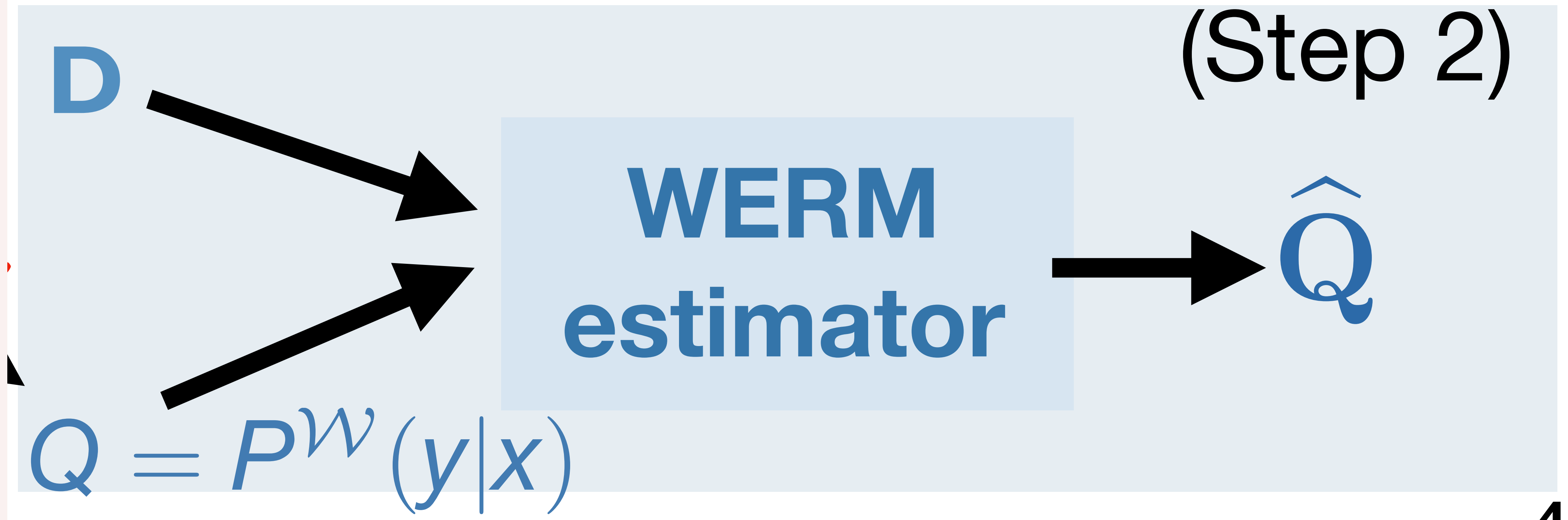

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Connection b/w non-igno. and WERM

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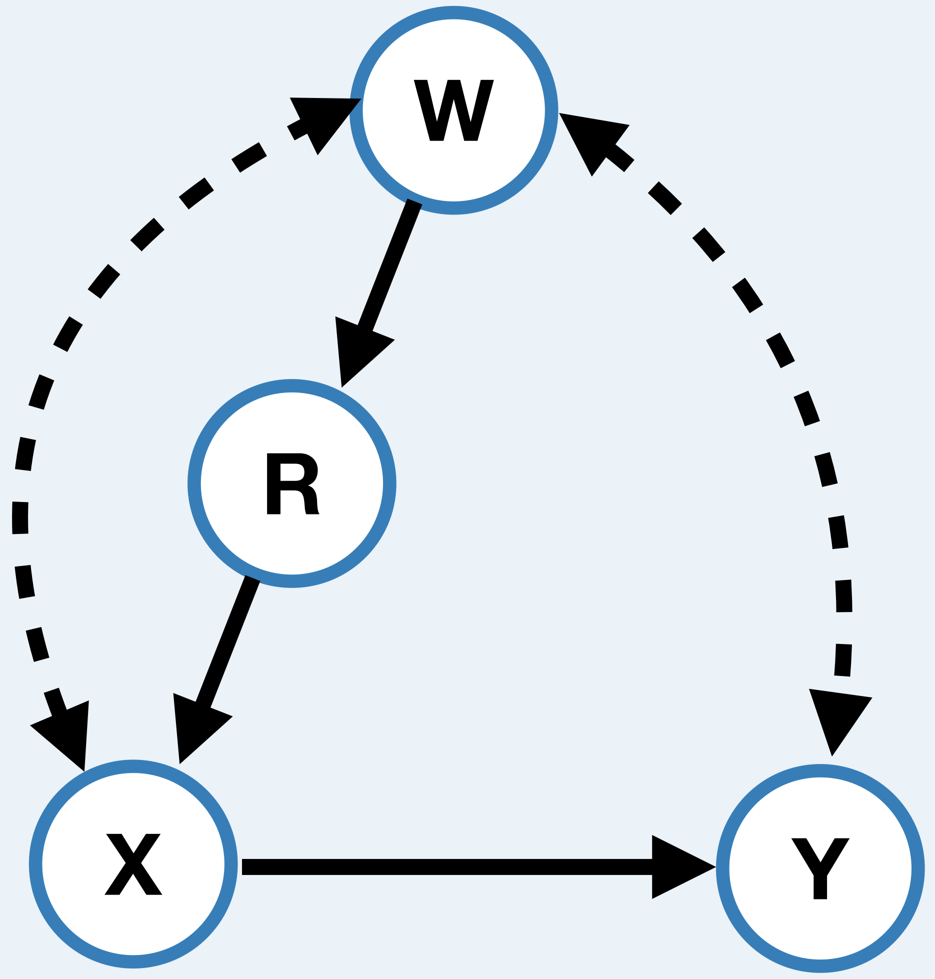
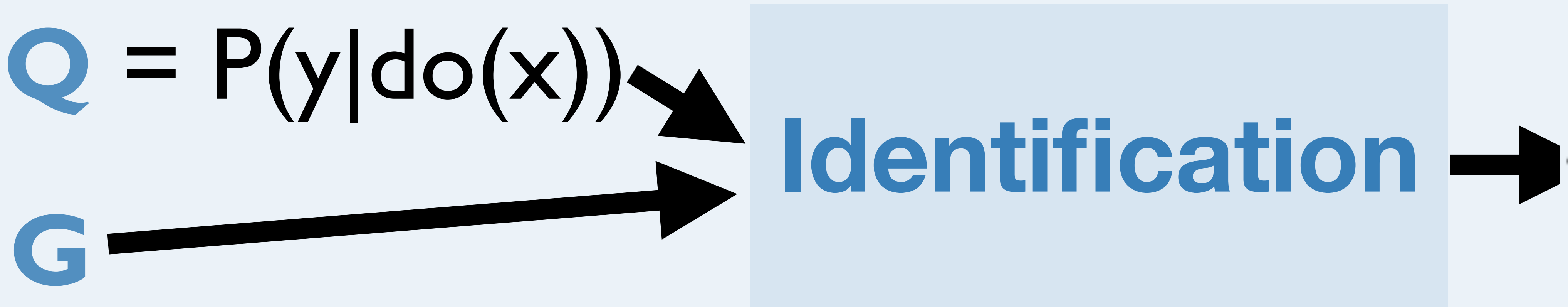
Practical Scenario on Non-igno. case (Example 1)



$$P(y|do(x)) = \frac{\sum_w P(y,x|r,w)P(w)}{\sum_w P(x|r,w)P(w)}$$

- The causal effect is identifiable, but the estimand is not a typical input for the WERM estimator.

(Step 1)



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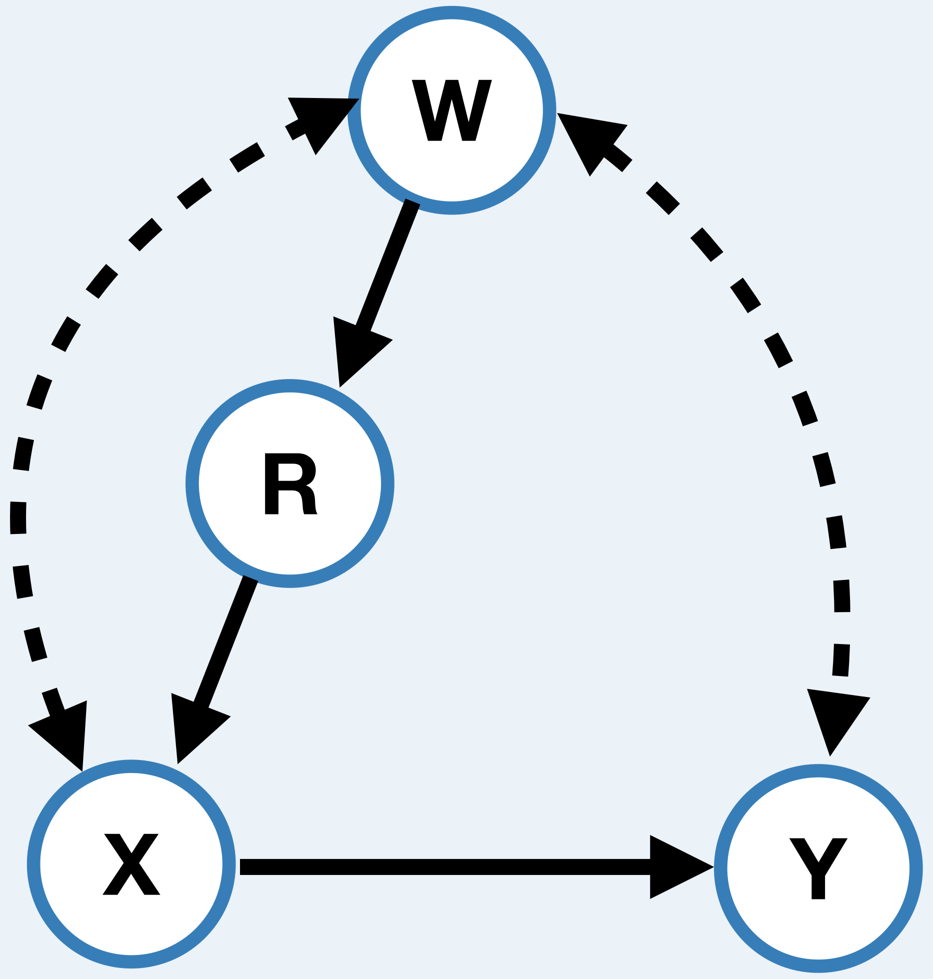

$$P(y|do(x)) = \frac{\sum_w P(y,x|r,w)P(w)}{\sum_w P(x|r,w)P(w)}$$

- The causal effect is identifiable, but the estimand is not a typical input for the WERM estimator.
- However, we can represent the query Q=P(y|do(x)) as a weighted distribution
- Taking W=P(r)/P(r|w). Then,

$$P(y|do(x)) = P^{\mathcal{W}}(y|x,r)$$

End-to-end solution to causal inference

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Contribution Filling the bridge between causal effect identification and the estimation

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Q = P(y|do(x)) **G**

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$(W^*, R) = \mathbf{wID}(Q, P, G)$

(Algo. 1)

such that

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Estimation (Sec. 4)

- Generalization bound (Prop. 1)
- Structural Risk Minimization (Thm. 2)

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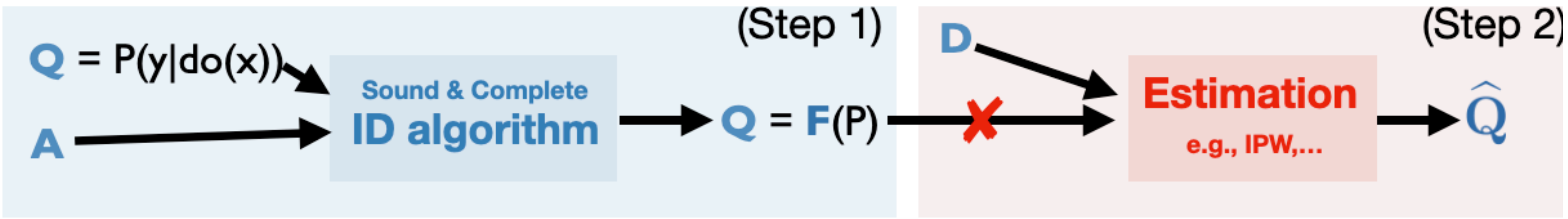

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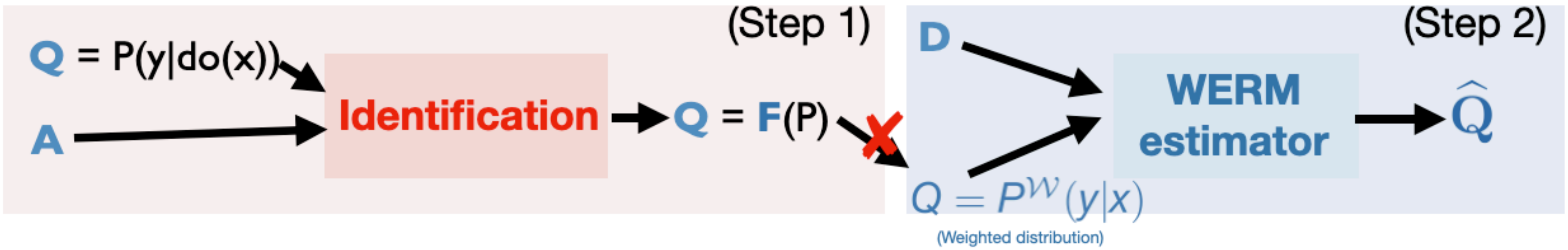

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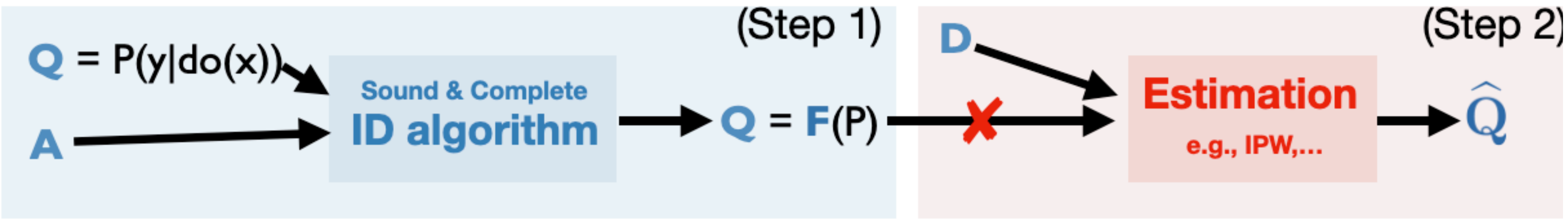

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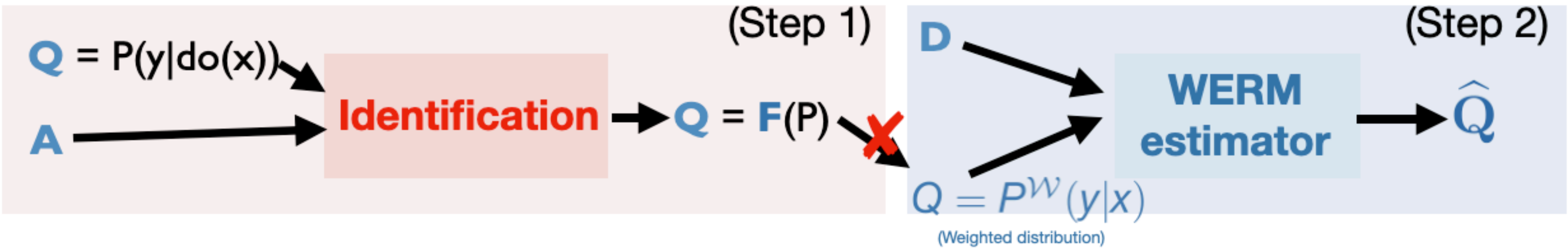

- We fill the gap between the causal inference and the ERM based estimation.