

# Directed Acyclic Graphs: Marginal Independence

STSCI / INFO / ILRST 3900: Causal Inference  
Fall 2024

24 Sep 2024

# Logistics

- ▶ 5 Flex days
- ▶ Help with R:
  - ▶ Guide pinned in Ed
  - ▶ Discussion section will walk through examples
- ▶ Groups for homework
- ▶ Project discussion tomorrow

# Learning goals for today

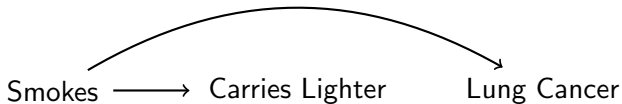
At the end of class, you will be able to

- ▶ draw a causal Directed Acyclic Graph
- ▶ enumerate edges in the graph
- ▶ read statistical dependence of nodes in the graph
- ▶ determine marginal exchangeability in the graph

After class:

- ▶ Hernán and Robins 2020 Chapter 6.1 and 6.2

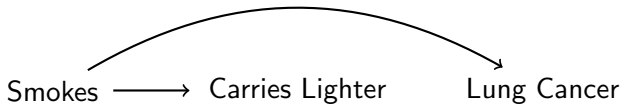
Directed Acyclic Graphs (DAGs) formalize **causal beliefs**



Causal beliefs:

- 1) Smoking may cause you to carry a lighter
- 2) Smoking may cause lung cancer
- 3) Carrying a lighter does not cause lung cancer

Directed Acyclic Graphs (DAGs) formalize **causal beliefs**



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**Nodes** represent random variables

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**Edges** represent direct causal effects

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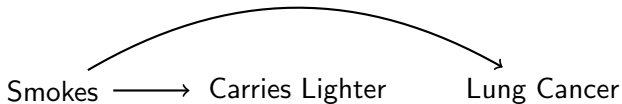
**Edges** represent direct causal effects

Additional Requirements

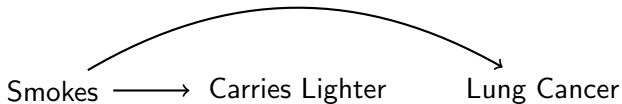
- In this class we will think about **acyclic** graphs
- Nodes with edges to at least two other nodes should be included



Directed Acyclic Graphs (DAGs) formalize **statistical dependence**



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(Smokes, Carries Lighter) are statistically dependent  
— because (Smokes) causes (Carries Lighter)

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(Smokes, Lung Cancer) are statistically dependent

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(Smokes, Lung Cancer) are statistically dependent

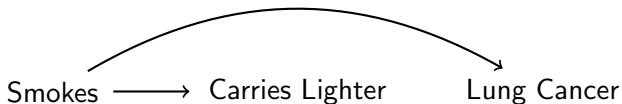
— because (Smokes) causes (Lung Cancer)

(Carries Lighter, Lung Cancer) are statistically dependent

— because (Smokes) causes both

**Task.** Propose a rule for when two nodes are dependent

Two nodes are dependent if and only if \_\_\_\_\_



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— because (Smokes) causes (Carries Lighter)

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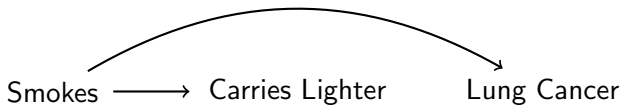
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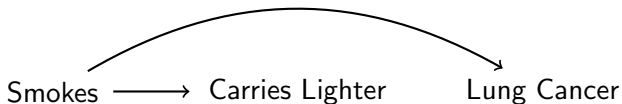
**Possible rule**

(not yet correct)

Two nodes are dependent if and only if  
they are connected by a path

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**Path**

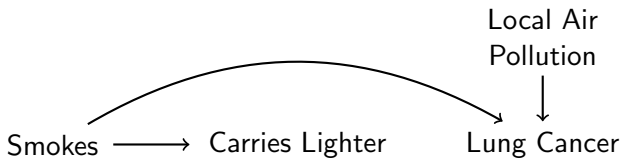
A sequence of edges connecting two nodes

Smokes  $\rightarrow$  Carries Lighter

Smokes  $\rightarrow$  Lung Cancer

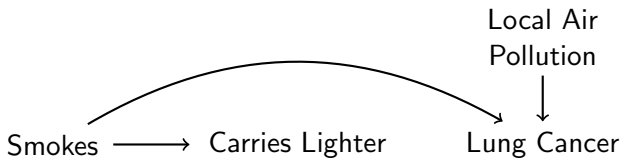
Carries Lighter  $\leftarrow$  Smokes  $\rightarrow$  Lung Cancer

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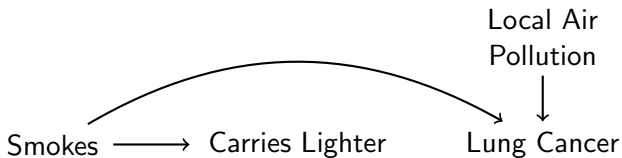


**Task.** Propose a rule for when two nodes are dependent



(Local Air Pollution) causes (Lung Cancer)

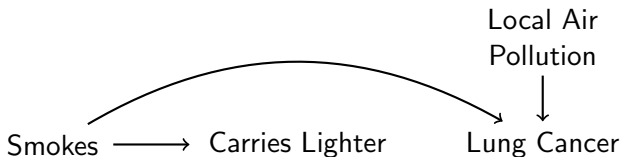
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(Local Air Pollution) causes (Lung Cancer)

There are no common causes of (Smokes, Local Air Pollution)

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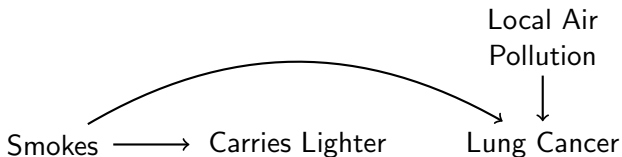


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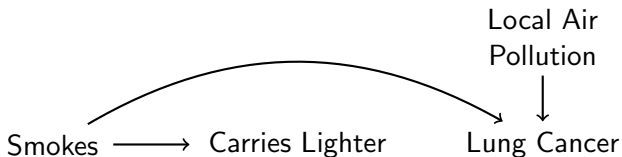
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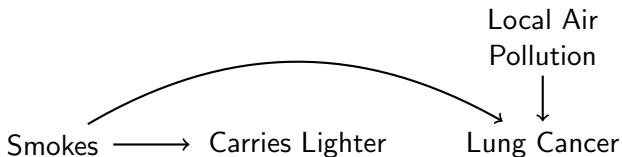
Is (Smokes) statistically related to (Local Air Pollution)?

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Lung cancer is a **collider** on the path  
(Smokes)  $\rightarrow$  (Lung Cancer)  $\leftarrow$  (Local Air Pollution)

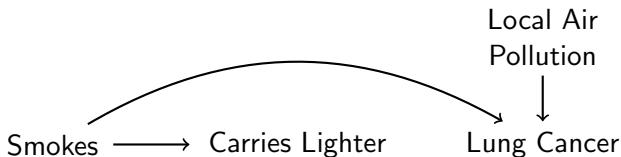
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**Collider**      A node on a path where two edges collide  $\rightarrow \bullet \leftarrow$

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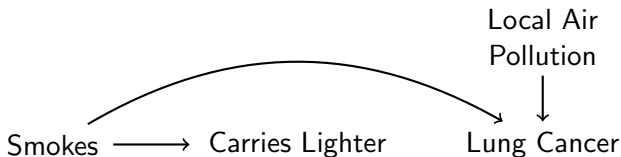
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A collider **blocks the path**.

A blocked path does not create statistical dependence.

**Task.** Propose a rule for when two nodes are dependent



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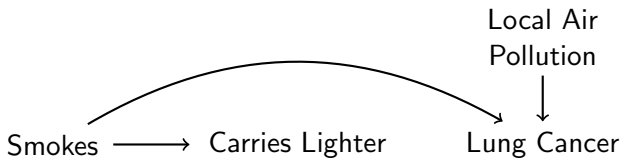
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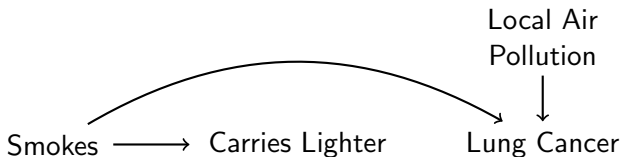
Intuition:      If two variables affect one outcome,  
that does not make those two variables related



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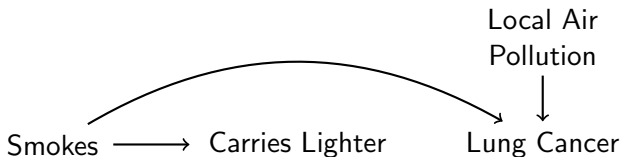


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**Rule**

Two nodes are dependent if and only if they are connected by an unblocked path (path with no colliders)

DAGs help us reason about exchangeability

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DAGs tell us why two variables are statistically dependent

- ▶ A set of unblocked paths

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Exchangeability requires statistical independence:  $A \perp\!\!\!\perp Y^a$

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# DAGs help us reason about exchangeability

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- ▶ A set of unblocked paths

Exchangeability requires statistical independence:  $A \perp\!\!\!\perp Y^a$

- ▶ Exchangeability holds if the only reason  $A$  and  $Y$  are related is the causal effect of  $A$  on  $Y$

Exchangeability holds if all unblocked paths between  $A$  and  $Y$  are causal paths that point from  $A$  to  $Y$

DAGs help us reason about exchangeability



# DAGs help us reason about exchangeability

## **Procedure**

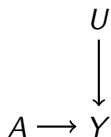
- 1) List all paths between  $A$  to  $Y$
- 2) Cross out the blocked paths
- 3) Exchangeability holds if all remaining paths are causal

# DAGs help us reason about exchangeability

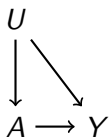
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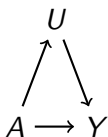
DAG 1



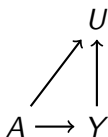
DAG 2



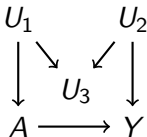
DAG 3



DAG 4



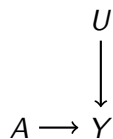
DAG 5



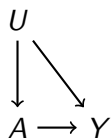
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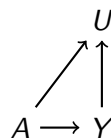
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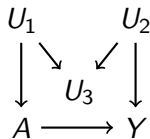
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