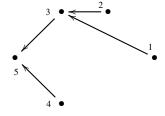
### Causality and directed acyclic graphs

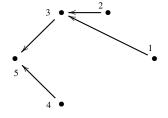
# Get to know and have some intuition about

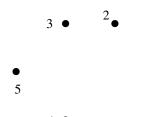
- Causality in philosophy (of science)
- Conditional independence relations
- Causal discovery algorithms
- Confounds and back doors



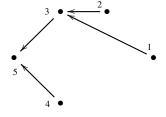
David Hume (1711-1776)

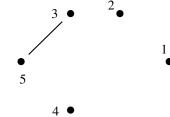


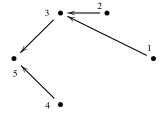




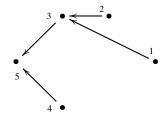
4 ●





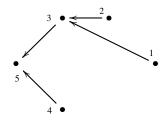


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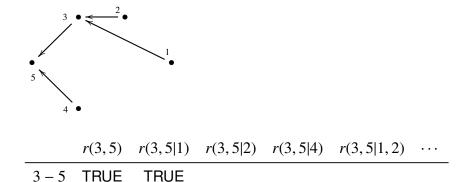
$$r(3,5)$$
  $r(3,5|1)$   $r(3,5|2)$   $r(3,5|4)$   $r(3,5|1,2)$  ···

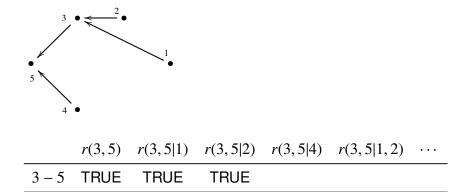
3 - 5

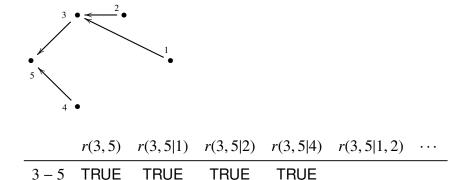


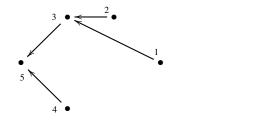
$$r(3,5)$$
  $r(3,5|1)$   $r(3,5|2)$   $r(3,5|4)$   $r(3,5|1,2)$  ···

3-5 TRUE

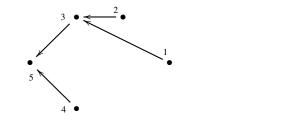




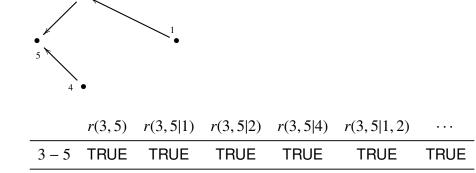




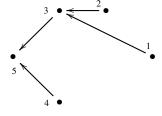
	r(3, 5)	r(3, 5 1)	r(3, 5 2)	r(3, 5 4)	r(3, 5 1, 2)	• • •
3 – 5	TRUE	TRUE	TRUE	TRUE	TRUE	



	r(3,3)	r(3,5 1)	r(3, 5 2)	r(3,5 4)	r(3,5 1,2)	•••
5	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE

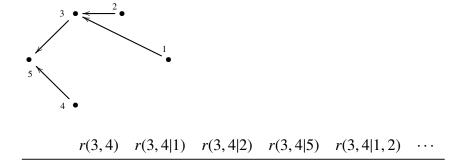


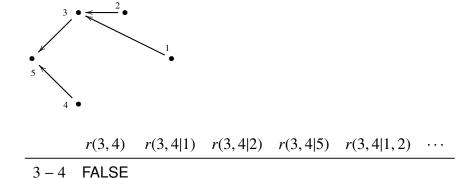
There is no (set of) node(s) x such that  $(3 \perp 5 \mid x)$  holds; and so connection 3-5 is TRUE

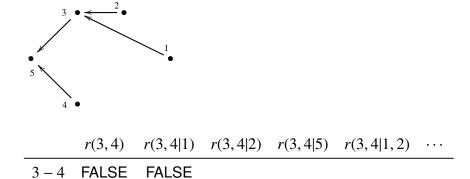


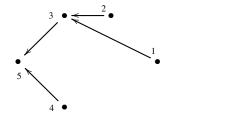
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3 - 4

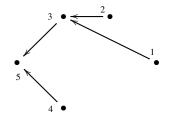




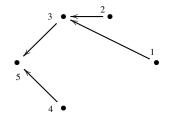




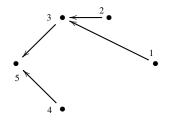
	r(3, 4)	r(3, 4 1)	r(3, 4 2)	r(3,4 5)	r(3,4 1,2)	• • •
3 – 4	FALSE	FALSE	FALSE			



	r(3,4)	r(3, 4 1)	r(3, 4 2)	r(3, 4 5)	r(3,4 1,2)	• • •
3 – 4	FALSE	FALSE	FALSE	TRUE		



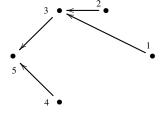
	r(3,4)	r(3, 4 1)	r(3, 4 2)	r(3,4 5)	r(3,4 1,2)	
3 – 4	FALSE	FALSE	FALSE	TRUE	FALSE	

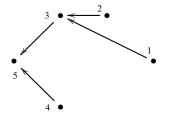


	r(3,4)	r(3, 4 1)	r(3, 4 2)	r(3, 4 5)	r(3,4 1,2)	• • •
3 – 4	FALSE	FALSE	FALSE	TRUE	FALSE	

No correlation between 3 and 4 and so no (direct) connection 3-4, but conditioning on 5 gives correlation r(3,4) and so a collider  $3 \rightarrow 5 \leftarrow 4$ .

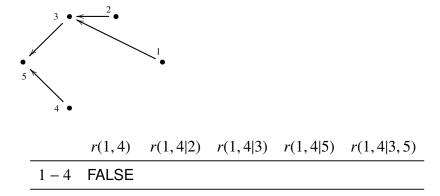
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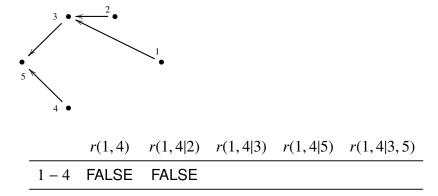


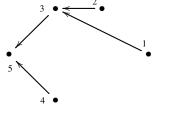


r(1,4)	r(1,4 2)	r(1,4 3)	r(1,4 5)	r(1,4 3,5)

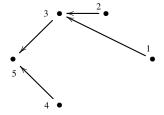
1 - 4



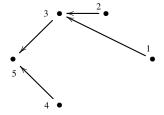




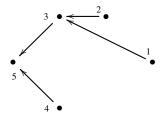
	r(1,4)	r(1,4 2)	r(1,4 3)	r(1,4 5)	r(1,4 3,5)
1 – 4	FALSE	FALSE	FALSE		



	r(1,4)	r(1,4 2)	r(1,4 3)	r(1,4 5)	r(1,4 3,5)
1 – 4	FALSE	FALSE	FALSE	TRUE	

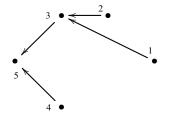


	r(1,4)	r(1,4 2)	r(1,4 3)	r(1,4 5)	r(1,4 3,5)
1 – 4	FALSE	FALSE	FALSE	TRUE	



	r(1, 4)	r(1, 4 2)	r(1,4 3)	r(1,4 5)	r(1,4 3,5)
1 – 4	FALSE	FALSE	FALSE	TRUE	

There is no correlation between 1 and 4, and so no (direct) connection 1-4.



	r(1, 4)	r(1, 4 2)	r(1,4 3)	r(1,4 5)	r(1,4 3,5)
1 – 4	FALSE	FALSE	FALSE	TRUE	FALSE

There is no correlation between 1 and 4, and so no (direct) connection 1-4.

No collider since conditioning on 3 and 5 removes the correlation again.

IC-Algorithm Pearl (1988)

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Input  $\hat{P}$  a sampled distribution

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Input  $\hat{P}$  a sampled distribution Output some acyclic graph for  $\hat{P}$ 

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**IC-Algorithm** Pearl (1988)

Input  $\hat{P}$  a sampled distribution Output some acyclic graph for  $\hat{P}$ 

- 1. For each pair a and b, look for  $(a \perp b \mid S_{ab})$ . If no such  $S_{ab}$  exists, then a and b are dependent.
- 2. For each trio (a, b, c) such that a c b check if c belongs to  $S_{ab}$ . If so, then nothing. If c is not in  $S_{ab}$  then make a collider at c, i.e.  $a \rightarrow c \leftarrow b$ .

IC-Algorithm Pearl (1988)

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- 3. Orient as many of the undirected edges as possible, subject to: (i) no new *v*-structures and (ii) no cycles.

**IC-algorithm** with multivariate normal (Gaussian) data

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For any X, Y, and Z that have a multivariate normal distribution, we have

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1. If *X* and *Y* are independent conditional on *Z* then they are conditionally uncorrelated, i.e. the partial correlation is 0.

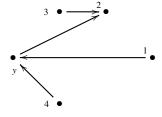
**IC-algorithm** with multivariate normal (Gaussian) data

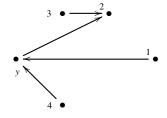
For any X, Y, and Z that have a multivariate normal distribution, we have

- 1. If *X* and *Y* are independent conditional on *Z* then they are conditionally uncorrelated, i.e. the partial correlation is 0.
- 2. If *X* and *Y* given *Z* have a partial correlation of 0, then they are conditionally independent.

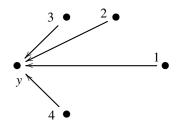


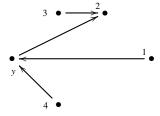
$$\Leftrightarrow \rho(X, Y \mid Z), \dots$$



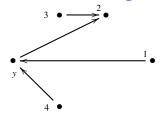


#### regression framework



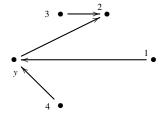


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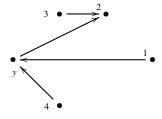
regression framework

$$r(y, 3|1, 2, 4)$$
  
 $y-3$ 



regression framework

	r(y, 3 1, 2, 4)
y-3	TRUE

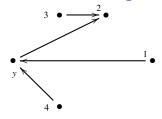


regression framework

	r(y, 3 1, 2, 4)
y-3	TRUE

False inference that 3 has influence on y

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regression framework

r(y, 3 1, 2, 4)
TRUE

False inference that 3 has influence on *y* Solution: Verify all combinations of partial correlations!

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