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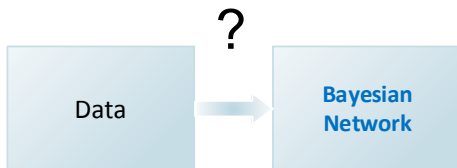
# Learning the Structure of Bayesian Networks

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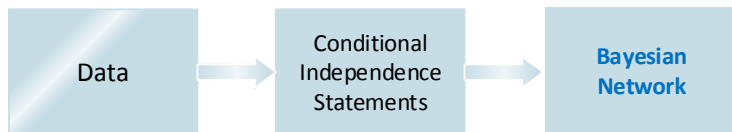
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- Assume that you are given a bunch of cases generated by some unknown Bayesian network  $N$  over the universe  $\mathcal{U}$  and you want to reconstruct the Bayesian network. What you will do is to learn the structure of the Bayesian network from the cases.



# Constraint Based Learning Methods

- The constraint based methods establish a set conditional independence statements holding for the data, and use this set to build a network with d-separation properties corresponding to the conditional independence properties determined [Jensen and Nielsen, 2007].

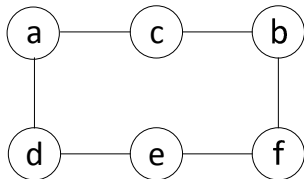


# Notation for Conditional Independence

- $I(a,b,\chi)$ :  $a$  is independent from  $b$  given  $\chi$
- $I(a,b)$ : shorthand for  $I(a,b,\phi)$
- $I(a,b,c)$ :  $a$  is independent from  $b$  given  $c$

# Notation for PC Algorithm

- $A_{Cab}$ : the set of nodes adjacent to  $a$  or to  $b$  in graph  $C$ , except for  $a$  and  $b$  themselves.
- $U_{Cab}$ : the set of nodes in graph  $C$  on (acyclic) undirected paths between  $a$  and  $b$ , except for  $a$  and  $b$  themselves.



$$A_{Cab} = \{c, d, f\}$$

$$U_{Cab} = \{c, d, e, f\}$$

$$A_{Cab} \cap U_{Cab} = \{c, d, f\}$$

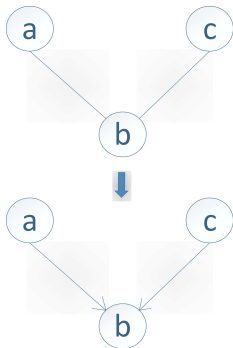
# PC Algorithm [Spirtes and Glymour, 1991]

- 1 From the complete undirected graph  $C$  on the nodes set  $V$ .
- 2  $i = 0$ .  
repeat
  - For each pair of nodes  $(a, b)$  adjacent in  $C$ , if  $A_{Cab} \cap U_{Cab}$  has cardinality greater than or equal to  $i$  and  $a, b$  are independent conditional on any subsets of  $A_{Cab} \cap U_{Cab}$  of cardinality less than  $i$ , delete  $a$ - $b$  from  $C$ .
  - $i = i + 1$
 until for each pair of adjacent nodes  $a, b$ ,  $A_{Cab} \cap U_{Cab}$  is of cardinality less than  $i$ .  
Call the resulting undirected graph  $F$ .
- 3 For each triple of nodes  $(a, b, c)$  such that the pair  $(a, b)$  and the pair  $(b, c)$  are each adjacent in  $F$  but the pair  $(a, c)$  are not adjacent in  $F$ , orient  $a$ - $b$ - $c$  as  $a \rightarrow b \leftarrow c$  if and only if  $a$  and  $c$  are dependent on every subset of  $A_{Fab} \cap U_{Fab}$  containing  $b$ . Output all graphs consistent with these orientations.

# learning skeleton of BN

- $i = 0$ ,  $I(a, b)$ ? If yes, remove the link  $(a, b)$
- $i = 1$ ,  $I(a, b, \{x\})$ ? If yes, remove the link  $(a, b)$ .  
 $\{x\}$  is any subset of  $A_{Dab} \cap U_{Dab}$  with one node.
- $i = 2$ ,  $I(a, b, \{x, y\})$ ? If yes, remove the link  $(a, b)$ .  
 $\{x, y\}$  is any subset of  $A_{Fab} \cap U_{Fab}$  with two nodes.
- ... ( until the cardinality of  $A_{Fab} \cap U_{Fab}$  is less than  $i$ .)

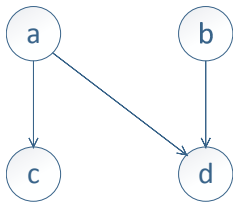
# orienting links



If and only if for every subset  $S$  of  $A_{Cac} \cap U_{Cac}$  containing  $b$ ,  $I(a, c, S) \rightarrow \text{Yes}$ .



## example



$I(a, b)$ ? Yes

$I(a, c)$ ? No

$I(a, d)$ ? No

$I(b, c)$ ? Yes

$I(b, d)$ ? No

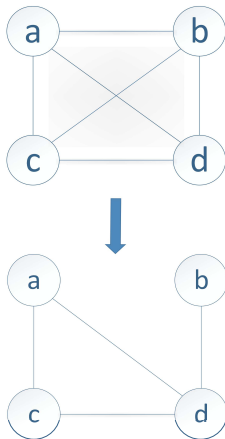
$I(c, d)$ ? No

$I(a, c, d)$ ? No

$I(a, d, c)$ ? No

$I(c, d, a)$ ? Yes

## example


 $i = 0$ 
 $I(a, b)$ ? Yes. remove (a, b)

 $I(a, c)$ ? No

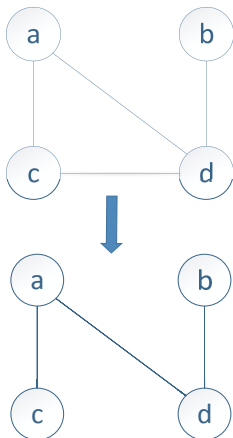
 $I(a, d)$ ? No

 $I(b, c)$ ? Yes. remove (b, c)

 $I(b, d)$ ? No

 $I(c, d)$ ? No

## example


 $i = 1$ 

$$A_{cac} \cap U_{cac} = \{d\}$$

 $l(a, c, d)?$  No

$$A_{cad} \cap U_{cad} = \{c\}$$

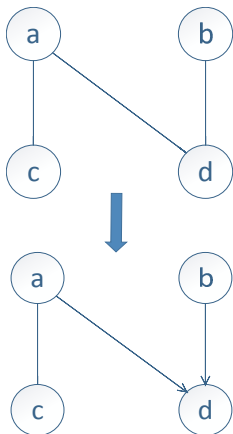
 $l(a, d, c)?$  No

$$A_{ccd} \cap U_{ccd} = \{a\}$$

 $l(c, d, a)?$  Yes. remove (c, d)

$$A_{cbd} \cap U_{cbd} = \phi$$

## example



$$A_{Cab} \cap U_{Cab} = \{d\}$$

$I(a, b, d)$ ? Yes  $\rightarrow$  converging connection

- Avoid new converging connection
- Avoid directed cycles

# References



Finn V.Jensen and Thomas D.Nielsen (2007)

*Bayesian Networks and Decision Graphs* Springer: NY, USA, 2007; 230 -236.



Peter Spirtes and Clark Glymour (1991)

An Algorithm for Fast Recovery of Sparse Causal Graphs

*Social Science Computer Review* 1991, Vol. 9, No.1, 62-72.