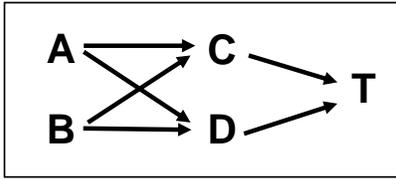


## An example of signature multiplicity due to small samples

Consider a simplified pathway structure and parameterization shown in the figure below. It involves 4 genes ( $A, B, C, D$ ) and a phenotypic response variable  $T$ . This network encodes a faithful distribution<sup>1</sup> and thus only one Markov boundary exists in large samples [1–4], which is  $\{C, D\}$ . Now consider that we have access to three small samples from this distribution such that: in sample #1 one cannot reliably establish that  $T \perp A | \{C, D\}$ , in sample #2 one cannot reliably establish that  $T \perp B | \{C, D\}$ , and in sample #3 one cannot reliably establish either  $T \perp A | \{C, D\}$  or  $T \perp B | \{C, D\}$ . Three Markov boundaries can be identified in the above samples,  $\{C, D, A\}$ ,  $\{C, D, B\}$ , and  $\{C, D, A, B\}$ , respectively, assuming that neither  $A$  nor  $B$  significantly decreases the predictivity of  $T$  in given samples.



$P(T   C, D)$	$(C = 0, D = 0)$	$(C = 0, D = 1)$	$(C = 1, D = 0)$	$(C = 1, D = 1)$
$T = 0$	0.2	0.5	0.7	0.4
$T = 1$	0.8	0.5	0.3	0.6

$P(C   A, B)$	$(A = 0, B = 0)$	$(A = 0, B = 1)$	$(A = 1, B = 0)$	$(A = 1, B = 1)$
$C = 0$	0.3	0.7	0.9	0.4
$C = 1$	0.7	0.3	0.1	0.6

$P(D   A, B)$	$(A = 0, B = 0)$	$(A = 0, B = 1)$	$(A = 1, B = 0)$	$(A = 1, B = 1)$
$D = 0$	0.6	0.7	0.8	0.4
$D = 1$	0.4	0.3	0.2	0.6

$P(A)$	
$A = 0$	0.6
$A = 1$	0.4

$P(B)$	
$B = 0$	0.4
$B = 1$	0.6

**Figure:** Example pathway structure with 4 gene variables ( $A, B, C, D$ ) and phenotypic response variable  $T$ . The structure is represented by a Bayesian network. The network parameterization is defined below the graph. All variables take values  $\{0,1\}$ .

<sup>1</sup> Let  $G$  be a graph and  $P$  a probability distribution. We will call a distribution  $P$  faithful to  $G$  if and only if every conditional independence relation true in  $P$  is entailed by the Markov Condition applied to  $G$ . In other words, the graph  $G$  using the Markov Condition provides an accurate map of all conditional and marginal dependencies and independencies in  $P$ . Recall that a probability distribution  $P$  satisfies the Markov Condition with respect to a graph  $G$  over variables  $\mathbf{V}$  if for every variable  $W$  in  $\mathbf{V}$ ,  $W$  is independent of all non-descendants of  $W$  given the parents of  $W$  [1].

## References

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