### Bayesian Networks

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#### Introduction

- ► Goal: Model causation (or more appropriatly probabilistic dependance) between correlated variables/ traits
- ▶ Plant breeding example: Given a dataset of many (10+) agronomic traits (plant height, nitrogen use efficiency, grain protein, grain carbohydrates/starch, leaf area index, radiation use effiency, yeild), how does selection for one (e.g. grain protein) impact another (e.g. grain yeild)?

# Graphical model terminology

- ▶ A graph (G = (V, A)) is composed of nodes (V) and vertices/arcs (A)
  - ▶ Nodes (*u*, *v*): variables or traits
  - Arcs (a = (u, v)): describe the relationships between nodes u and v
    - If u and v are ordered then the arc is directed, u and v unordered then the arc is undirected.
- Undirected graphs: no ordering between nodes; Directed graphs: all arcs are ordered; Partially directed graphs: some arcs are ordered
- ▶ Paths: sequences of arcs connecting two nodes; passes through each arc only once and all arcs follow the same direction
- Root and leaf nodes are the base and terminal nodes, respectively. No nodes are incoming for roots and no arcs leave leaf nodes.

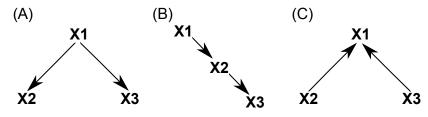
#### PICTURE OF NETWORKS

### Bayesian background

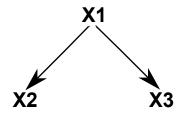
- ► Chain rule: Joint probability distribution of i random variables  $(x_1, x_2, x_3, x_4)$  is  $P(x_1, x_2, x_3, x_4) = P(x_4|x_1, x_2, x_3)P(x_3|x_1, x_2)P(x_2|x_1)P(x_1)$
- ▶ If we have no knowledge of any variables then variables are independent if  $P(x_1, x_2, x_3, x_4) = P(x_4)P(x_3)P(x_2)P(x_1)$
- ▶ If we have knowledge of some variable  $(x_4)$  then variables are independent if  $P(x_1, x_2, x_3|x_4) = P(x_3|x_4)P(x_2|x_4)P(x_1|x_4)$

$$P(x_1, x_2, x_3 | x_4) = \frac{P(x_3 | x_4) P(x_2 | x_4) P(x_1 | x_4) P(x_4)}{P(x_4)}$$

- ▶ BN are a class of graphical models that represent the probabilistic dependencies between a set of random variables as a directed acyclic graph (no loops!). We can scale these concepts to a graphical model.
- For a divergent structure (A) the joint distribution is P(X1, X2, X3) = P(X2|X1)P(X3|X1)P(X1); serial structure (B) the joint distribution is P(X1, X2, X3) = P(X3|X2)P(X2|X1)P(X1); convergent structure (C) the joint distribution is P(X1, X2, X3) = P(X2|X1, X3)P(X1)P(X3)

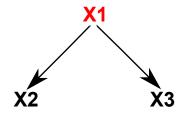


► **Example 1**: If we have no information for the divergent structure, are X2 and X3 independent?



$$P(X2, X3) = \sum_{X3} P(X2|X1)P(X3|X1)P(X1)$$

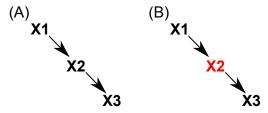
► Example 2: If we have information on X1 for the divergent structure, are X2 and X3 independent?



$$P(X2, X3|X1) = P(X2|X1)P(X3|X1)$$

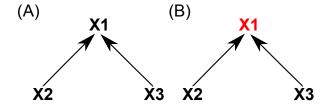
#### Example 3:

- 1. If we don't have information on X2 for the serial structure (A), are X1 and X3 independent?  $P(X1, X3) = \sum_{X2} P(X3|X2)P(X2|X1)P(X1)$
- 2. If we do have information on X2 for the serial structure (B), are X1 and X3 independent? P(X1, X3|X2) = P(X3|X2)P(X1|X2)



#### Example 4:

- 1. If we don't have information on X1 for the convergent structure (A), are X2 and X3 independent? P(X2, X3) = P(X2)P(X3)
- 2. If we do have information on X1 for the convergent structure (B), are X2 and X3 independent?  $P(X1, X3|X2) = \frac{P(X3)P(X3)P(X1|X2,X3)}{P(X1)}$



### Rules for direct-separation

- If we scale this up, each node can be considered a subset of nodes in a DAG
- Consider only the cases where we have information. Given some information for a group of nodes (B), the two subsets of nodes A and C are conditionally independant if there is a node w that has (1) converging arrows and w nor any of its descendants are part of B (e.g. does not carry information), or if w does not have converging arrows and is a part of B
- If these conditions are satisfied we can say that B direct-separates (d-separates) A from C