Causal graphs

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- causal graphs = directed acyclic graphs (DAG) are useful for causal inference
  - ↳ identify which variables to control for
- they make assumptions btw. variables explicit

Directed graph: $A \to Y$ (A affects Y)

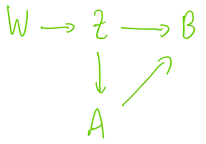
→ causal direction is known/visible ↳ arrow makes this graph directed

(e.g. A – Y is undirected graph)

- graphical models:
  - encode relationships among variables
  - ↳ graph tells us: which variables are independent, dependent, conditionally independent, etc. ...

Terminology: $A \to Y$ (a directed graph b/c all edges are directed)

- A affects Y
- A, Y ... nodes / vertices / set of variables
- → ... edge (link), indicates a direction (i.e. directed path)
- adjacency / adjacent ... nodes connected by an edge are called adjacent



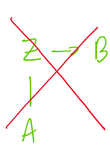
paths from W to B:
- $W \to Z \to B$ (1)
- $W \to Z \to A \to B$ (2)

paths from Z to W:
- $Z \leftarrow W$

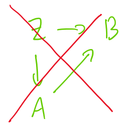
- a path is a way to get from one node to another node, traveling along edges

Directed acyclic graph (DAG):

- no undirected paths →

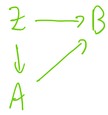


- no cycles →



(does not adhere to DAG conditions)

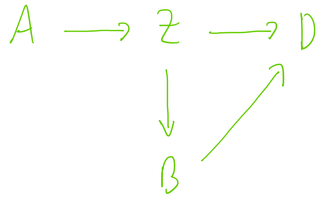
- valid DAG example:



✓ (all directed, no cycle / loop)

THIS CLASS: DAGs only (i.e. graph = DAG)

Further terminology:



- parents (A is a parent of Z)
- children (B is a child of Z)
- ancestors (higher level parents) (D is a descendent of A)
- descendants (higher level children) (Z is an ancestor of D, A is an ancestor of D)

- node D has 2 parents, B and Z

- we use DAGs to determine set of variables that we need to control for i.o. to achieve the ignorability assumption