

Syllabus, Chapter 3:

Independences and Graphical Representations

A qualitative notion of independence

Observation:

People are capable of making statements about independences among variables without having to perform numerical calculations.

Conclusion:

In human reasoning behaviour, the qualitative notion of independence is more fundamental than the quantitative notion of independence.

The independence relation of joint distribution \Pr

Definition: Let V be a set of random variables and let \Pr be a joint probability distribution on V .

The independence relation I_{\Pr} of \Pr is a set $I_{\Pr} \subseteq \mathcal{P}(V) \times \mathcal{P}(V) \times \mathcal{P}(V)$, defined for all $X, Y, Z \subseteq V$ by

$$(X, Z, Y) \in I_{\Pr} \text{ if and only if } \Pr(X \mid Y \wedge Z) = \Pr(X \mid Z)$$

Remarks:

- $(X, Z, Y) \in I_{\Pr}$ will be written as $I_{\Pr}(X, Z, Y)$;
 $(X, Z, Y) \notin I_{\Pr}$ will be written as $\neg I_{\Pr}(X, Z, Y)$;
- a statement $I_{\Pr}(X, Z, Y)$ is called an independence statement for the joint distribution \Pr .

Properties of I_{Pr} : symmetry

Lemma: $I_{Pr}(\mathbf{X}, \mathbf{Z}, \mathbf{Y})$ if and only if $I_{Pr}(\mathbf{Y}, \mathbf{Z}, \mathbf{X})$

Proof: [NB This is an exercise from the Syllabus. In proofs you should also explain your steps, like done in the lectures.]

$$\begin{aligned} I_{Pr}(\mathbf{X}, \mathbf{Z}, \mathbf{Y}) &\iff \Pr(\mathbf{X} \mid \mathbf{Y} \wedge \mathbf{Z}) = \Pr(\mathbf{X} \mid \mathbf{Z}) \\ &\iff \frac{\Pr(\mathbf{X} \wedge \mathbf{Y} \wedge \mathbf{Z})}{\Pr(\mathbf{Y} \wedge \mathbf{Z})} = \frac{\Pr(\mathbf{X} \wedge \mathbf{Z})}{\Pr(\mathbf{Z})} \\ &\iff \frac{\Pr(\mathbf{X} \wedge \mathbf{Y} \wedge \mathbf{Z})}{\Pr(\mathbf{X} \wedge \mathbf{Z})} = \frac{\Pr(\mathbf{Y} \wedge \mathbf{Z})}{\Pr(\mathbf{Z})} \\ &\iff \Pr(\mathbf{Y} \mid \mathbf{X} \wedge \mathbf{Z}) = \Pr(\mathbf{Y} \mid \mathbf{Z}) \\ &\iff I_{Pr}(\mathbf{Y}, \mathbf{Z}, \mathbf{X}) \end{aligned}$$



Properties of I_{Pr} : decomposition

Lemma: $I_{Pr}(\mathbf{X}, \mathbf{Z}, \mathbf{Y} \cup \mathbf{W}) \Rightarrow I_{Pr}(\mathbf{X}, \mathbf{Z}, \mathbf{Y}) \wedge I_{Pr}(\mathbf{X}, \mathbf{Z}, \mathbf{W})$

Proof: (sketch) (Note: for $U = \mathbf{Y} \cup \mathbf{W}$, $c_U = c_Y \wedge c_W$!)

Suppose that

$\Pr(\mathbf{X} \mid \mathbf{Y} \wedge \mathbf{W} \wedge \mathbf{Z}) = \Pr(\mathbf{X} \mid \mathbf{Z})$. Then, by definition,

$$\Pr(\mathbf{X} \wedge \mathbf{Y} \wedge \mathbf{W} \wedge \mathbf{Z}) = \Pr(\mathbf{Y} \wedge \mathbf{W} \wedge \mathbf{Z}) \cdot \frac{\Pr(\mathbf{X} \wedge \mathbf{Z})}{\Pr(\mathbf{Z})}$$

For $\Pr(\mathbf{X} \mid \mathbf{Y} \wedge \mathbf{Z})$ we find that

$$\begin{aligned}\Pr(\mathbf{X} \mid \mathbf{Y} \wedge \mathbf{Z}) &= \frac{\Pr(\mathbf{X} \wedge \mathbf{Y} \wedge \mathbf{Z})}{\Pr(\mathbf{Y} \wedge \mathbf{Z})} \\ &= \frac{\sum_{c_W} \Pr(\mathbf{X} \wedge \mathbf{Y} \wedge \mathbf{Z} \wedge c_W)}{\Pr(\mathbf{Y} \wedge \mathbf{Z})} \\ &= \frac{\Pr(\mathbf{X} \wedge \mathbf{Z})}{\Pr(\mathbf{Z})} = \Pr(\mathbf{X} \mid \mathbf{Z})\end{aligned}$$



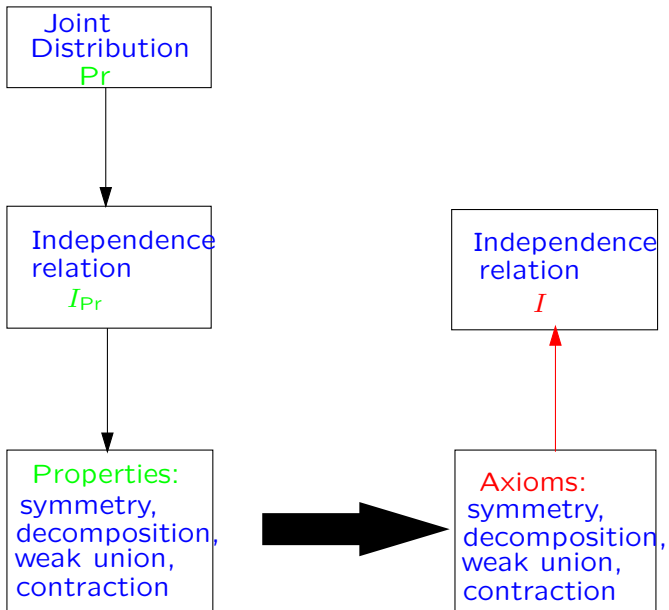
Properties of I_{Pr} : weak union, contraction

Lemma:

- if $I_{Pr}(X, Z, Y \cup W)$ then $I_{Pr}(X, Z \cup W, Y)$ (weak union);
- if $I_{Pr}(X, Z, W)$ and $I_{Pr}(X, Z \cup W, Y)$ then $I_{Pr}(X, Z, Y \cup W)$ (contraction)
- (for strictly positive Pr also the intersection property holds; see syllabus)

Proof: left as exercise 3.1.

Defining a qualitative independence relation



The (qualitative) independence relation I

Definition:

Let V be a set of random variables and let $X, Y, Z, W \subseteq V$.

An independence relation I on V is a ternary relation $I \subseteq \mathcal{P}(V) \times \mathcal{P}(V) \times \mathcal{P}(V)$ that satisfies the following *axioms*:

① **symmetry:**

if $I(X, Z, Y)$ then $I(Y, Z, X)$;

② **decomposition:**

if $I(X, Z, Y \cup W)$ then $I(X, Z, Y)$ and $I(X, Z, W)$;

③ **weak union:**

if $I(X, Z, Y \cup W)$ then $I(X, Z \cup W, Y)$;

④ **contraction :**

if $I(X, Z, W)$ and $I(X, Z \cup W, Y)$ then $I(X, Z, Y \cup W)$.

An example

Lemma:

Let I be an independence relation on a set of random variables V . We have that for all $X, Y, Z, W \subseteq V$:

if $I(X, Z, Y)$ and $I(X \cup Z, Y, W)$ then $I(X, Z, W)$

Proof: (Note: we have no Pr , just the axioms!)

We observe that

$$\begin{aligned} I(X \cup Z, Y, W) &\Rightarrow_{\text{symm}} I(W, Y, X \cup Z) \Rightarrow_{\text{weakunion}} \\ &\Rightarrow I(W, Y \cup Z, X) \Rightarrow_{\text{symm}} I(X, Y \cup Z, W) \end{aligned}$$

From $I(X, Z, Y)$, $I(X, Y \cup Z, W)$ and the contraction axiom we have that $I(X, Z, W \cup Y)$; decomposition now gives $I(X, Z, W)$. ■

Representing independences

Different ways exist of representing an independence relation:

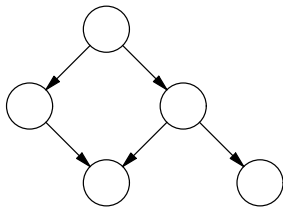
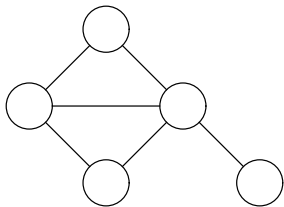
- explicitly list all independence statements of the relation;
- explicitly list only the independence statements of a suitable subset of the relation (the ‘basis’) — all other statements are implicitly represented by means of the axioms;
- code the independence relation in a graph;
- ...

An example

Consider $V = \{V_1, V_2, V_3, V_4\}$ and independence relation I on V :

$I(\{V_1\}, \emptyset, \{V_4\})$	$I(\{V_2\}, \emptyset, \{V_1\})$	$I(\{V_4\}, \{V_1\}, \{V_2\})$
$I(\{V_2\}, \emptyset, \{V_4\})$	$I(\{V_1, V_4\}, \emptyset, \{V_2\})$	$I(\{V_4\}, \{V_1\}, \{V_3\})$
$I(\{V_3\}, \emptyset, \{V_4\})$	$I(\{V_2, V_4\}, \emptyset, \{V_1\})$	$I(\{V_4\}, \{V_1\}, \{V_2, V_3\})$
$I(\{V_4\}, \emptyset, \{V_1\})$	$I(\{V_2\}, \emptyset, \{V_1, V_4\})$	$I(\{V_1\}, \{V_2\}, \{V_4\})$
$I(\{V_4\}, \emptyset, \{V_2\})$	$I(\{V_1\}, \emptyset, \{V_2, V_4\})$	$I(\{V_3\}, \{V_2\}, \{V_4\})$
$I(\{V_4\}, \emptyset, \{V_3\})$	$I(\{V_2\}, \{V_1\}, \{V_4\})$	$I(\{V_1, V_3\}, \{V_2\}, \{V_4\})$
$I(\{V_1, V_2\}, \emptyset, \{V_4\})$	$I(\{V_3\}, \{V_1\}, \{V_4\})$	$I(\{V_4\}, \{V_2\}, \{V_1\})$
$I(\{V_1, V_3\}, \emptyset, \{V_4\})$	$I(\{V_2, V_3\}, \{V_1\}, \{V_4\})$	$I(\{V_4\}, \{V_2\}, \{V_3\})$
$I(\{V_2, V_3\}, \emptyset, \{V_4\})$	$I(\{V_4\}, \{V_1, V_2\}, \{V_3\})$	$I(\{V_4\}, \{V_2\}, \{V_1, V_3\})$
$I(\{V_4\}, \emptyset, \{V_1, V_2\})$	$I(\{V_2\}, \{V_1, V_3\}, \{V_4\})$	$I(\{V_1\}, \{V_3\}, \{V_4\})$
$I(\{V_4\}, \emptyset, \{V_1, V_3\})$	$I(\{V_4\}, \{V_1, V_3\}, \{V_2\})$	$I(\{V_2\}, \{V_3\}, \{V_4\})$
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$I(\{V_1, V_2, V_3\}, \emptyset, \{V_4\})$	$I(\{V_4\}, \{V_2, V_3\}, \{V_1\})$	$I(\{V_1\}, \{V_4\}, \{V_2\})$
$I(\{V_4\}, \emptyset, \{V_1, V_2, V_3\})$	$I(\{V_4\}, \{V_3\}, \{V_1, V_2\})$	$I(\{V_2\}, \{V_4\}, \{V_1\})$
$I(\{V_1\}, \emptyset, \{V_2\})$	$I(\{V_4\}, \{V_3\}, \{V_1\})$	$I(\{V_3\}, \{V_1, V_2\}, \{V_4\})$

Coding an independence relation with a graph



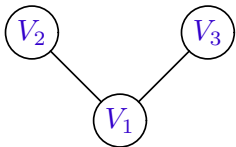
The global idea of coding an independence relation I on V in graph G :

- each variable $V_i \in V$ corresponds to a node $V_i \in V_G$;
- (combinations of) edges/arcs define a graphical notion of (d-)separation;
- there exists a mapping between (d-)separation and relation I

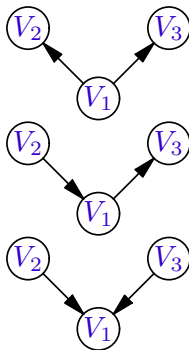
In the lectures, we from here on focus on $I_{Pr} \subset I$.

Graphs as a language for coding *I*

The directed graph provides a more expressive language than the undirected graph:



vs.



Example reasoning patterns



- do arcs capture causality? **not necessarily**
- do reasoning patterns really differ? **last differs from first two**
- what if we drop the direction of the arcs? **last one incomplete**

“Intercausal” interaction

Consider an experiment with two coins and a bell: the bell sounds iff the two coins have the same outcome after a toss.

Consider: variable C_1 : the outcome of tossing coin one;
variable C_2 : the outcome of tossing coin two;
variable B : whether or not the bell sounds;
independence relation I for this experiment.

We have, among others, that

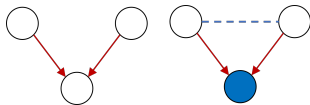
$$\begin{aligned} I_{\text{Pr}}(\{C_1\}, \emptyset, \{C_2\}) & \quad \neg I_{\text{Pr}}(\{C_1\}, \{B\}, \{C_2\}) \\ I_{\text{Pr}}(\{C_1\}, \emptyset, \{B\}) & \quad \neg I_{\text{Pr}}(\{C_1\}, \{C_2\}, \{B\}) \\ I_{\text{Pr}}(\{C_2\}, \emptyset, \{B\}) & \quad \neg I_{\text{Pr}}(\{C_2\}, \{C_1\}, \{B\}) \end{aligned}$$

This independence relation is an example of an independence relation with what is called an induced ‘dependency’.

Directed versus undirected graph language

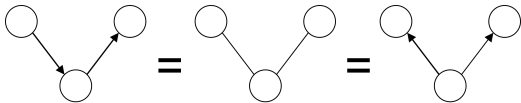
Arc directions encode the possibility of induced dependencies:

- a **head-to-head** node captures the possible occurrence of an “intercausal” interaction between its parents:



Note:

An acyclic(!) directed graph **without** head-to-head nodes encodes the **same** independences as its underlying undirected graph:



Undirected graphs: separation and (in)dependence

The lectures and the examination focus on directed graphical models. However, the concept of separation in undirected graphs is easier than the concept of d-separation in directed graphs, so you may want to study undirected graphs first. Both course syllabus and these slides (with accompanying video) provide the necessary information and exercises for that.

▶ Skip to directed graphs

The separation criterion: introduction

Definition:

Let $G = (V_G, E_G)$ be an undirected graph with edges E_G and nodes $V_G = \{V_1, \dots, V_n\}$, $n > 1$.

Let s be a path in G from a node V_i to a node V_j .

The path s is blocked by a set of nodes $Z \subseteq V_G$, if at least one node from Z is on the path s .

If s is not blocked by Z , the path is called active given Z .

The separation criterion

Definition:

Let $G = (V_G, E_G)$ be an undirected graph. Let $X, Y, Z \subseteq V_G$ be sets of nodes in G .

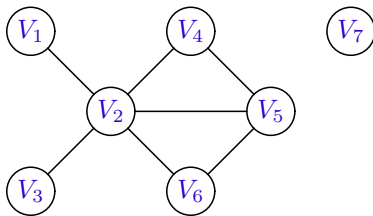
The set Z separates the set X from Y in G — Notation:

$\langle X | Z | Y \rangle_G$ — if every simple path in G from a node in X to a node in Y is blocked by Z .

Remarks:

- the above notion is known as the separation criterion for undirected graphs;
- if there is no path between the nodes X and Y in a graph G , then $\langle X | \emptyset | Y \rangle_G$.

An example



Which of the following separation statements are valid?

- a) $\langle \{V_1\} \mid \{V_2\} \mid \{V_3, V_6\} \rangle_G$ e) $\langle \{V_1, V_5, V_6\} \mid \emptyset \mid \{V_7\} \rangle_G$
b) $\langle \{V_4\} \mid \{V_2, V_5\} \mid \{V_6\} \rangle_G$ f) $\langle \{V_2\} \mid \{V_5\} \mid \{V_7\} \rangle_G$
c) $\langle \{V_4\} \mid \{V_1, V_2, V_5\} \mid \{V_6\} \rangle_G$ g) $\langle \{V_1\} \mid \{V_5\} \mid \{V_2\} \rangle_G$
d) $\langle \{V_1\} \mid \{V_4\} \mid \{V_5\} \rangle_G$

Answer: all except d) and g)

Independence relations and undirected graphs

Definition: Let I be an independence relation on a set of random variables V . Let $G = (V_G, E_G)$ be an undirected graph with $V_G = V$.

- graph G is called a **dependency map (D-map)** for I_{Pr} if for all $X, Y, Z \subseteq V$ we have:

$$\text{if } I_{Pr}(X, Z, Y) \text{ then } \langle X \mid Z \mid Y \rangle_G;$$

- graph G is called an **independency map (I-map)** for I_{Pr} if for all $X, Y, Z \subseteq V$ we have:

$$\text{if } \langle X \mid Z \mid Y \rangle_G \text{ then } I_{Pr}(X, Z, Y);$$

- graph G is called a **perfect map (P-map)** for I_{Pr} if G is both a dependency map and an independency map for I_{Pr} .

undirected D-maps: what can they tell?

Let I_{P_r} be an independence relation and G an undirected graph.

Consider a D-map for I_{P_r} , then

V_1 and V_2 neighbours² $\implies V_1, V_2$ dependent

V_1 and V_2 non-neighbours \implies ?? V_1 and V_2 can be:
dependent,
independent, or
conditionally independent

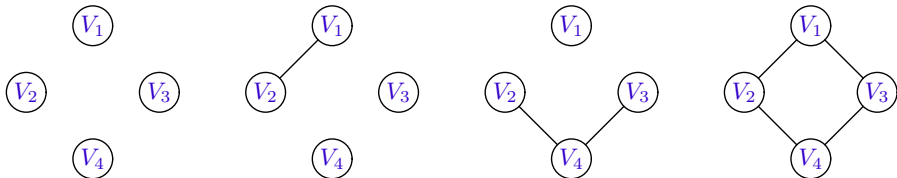
²i.e. directly connected by an edge

An example

Consider the independence relation I_{Pr} on $V = \{V_1, \dots, V_4\}$, defined by

$$I_{Pr}(\{V_1\}, \{V_2, V_3\}, \{V_4\}) \text{ and } I_{Pr}(\{V_2\}, \{V_1, V_4\}, \{V_3\})$$

Which of the following undirected graphs are examples of D-maps for I_{Pr} ?



See Exercise 3.5 (Syllabus) Answer: all

Undirected I-maps: what can they tell?

Let I_{Pr} be an independence relation and G an undirected graph.

Consider an I-map for I_{Pr} , then

V_1 and V_2 non-neighbours $\implies V_1, V_2$ (condit.) independent

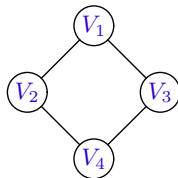
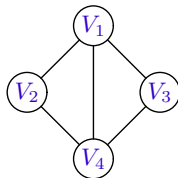
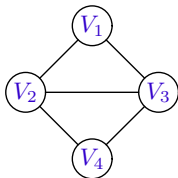
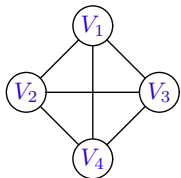
V_1 and V_2 neighbours \implies ?? V_1 and V_2 can be
dependent,
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An example

Consider the independence relation I_{Pr} on $V = \{V_1, \dots, V_4\}$, defined by

$$I_{Pr}(\{V_1\}, \{V_2, V_3\}, \{V_4\}) \text{ and } I_{Pr}(\{V_2\}, \{V_1, V_4\}, \{V_3\})$$

Which of the following undirected graphs are examples of I-maps for I_{Pr} ?



(See Exercise 3.5) Answer: all

Properties of I

Let I be an independence relation on a set of random variables \mathbf{V} .

Lemma:

Every independence relation I has an undirected D-map.

Proof:

The undirected graph $G = (\mathbf{V}, \emptyset)$ is a D-map for I . ■

Lemma:

Every independence relation I has an undirected I-map.

Proof:

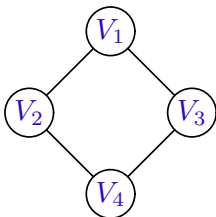
The undirected graph $G' = (\mathbf{V}, \mathbf{V} \times \mathbf{V})$ is an I-map for I . ■

An example

Consider the independence relation I_{Pr} on $V = \{V_1, \dots, V_4\}$, defined by

$$I_{Pr}(\{V_1\}, \{V_2, V_3\}, \{V_4\}) \text{ and } I_{Pr}(\{V_2\}, \{V_1, V_4\}, \{V_3\})$$

The following undirected graph is a perfect map for I_{Pr} :



Is this P-map **unique** ?

Does **every** I_{Pr} have a P-map ?

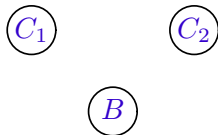
Answer: yes

Answer: no, see next slide

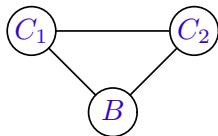
An example

Reconsider the experiment with the two coins and the bell.

- the following graph is the only D-map for the independence relation I_{Pr} of this experiment:



- the following graph is the only I-map for I_{Pr} :



- I_{Pr} does not have a perfect map !

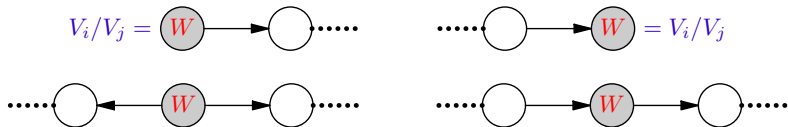
Directed acyclic graphs: d-separation and (in)dependence

The d-separation criterion: introduction

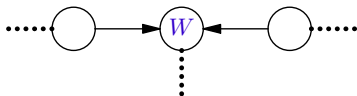
Definition: Let $G = (V_G, A_G)$ be an acyclic directed graph (DAG), and let s be a chain in G between V_i and $V_j \in V_G$.

Chain s is blocked (or: in-active) by a set $Z \subseteq V_G$ if s contains a node W for which one of the following holds:

- $W \in Z$ and W has at most one incoming arc on chain s :

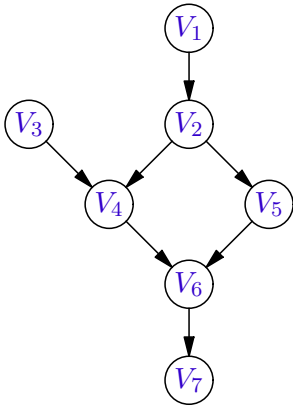


- $\sigma^*(W) \cap Z = \emptyset$ and W has two incoming arcs on chain s :



An example

Consider the following DAG and some of its chains:



- 1) V_4, V_2, V_5 from V_4 to V_5
- 2) V_1, V_2, V_5, V_6, V_7 from V_1 to V_7
- 3) V_3, V_4, V_6, V_5 from V_3 to V_5
- 4) V_2, V_4 from V_2 to V_4

Which chains are blocked by which of the following sets?

$\emptyset, \{V_2\}, \{V_5\}, \{V_2, V_5\},$
 $\{V_4\}, \{V_6\}, \{V_4, V_6\}, \{V_7\}$

Answers: \emptyset : 3; $\{V_2\}$: all; $\{V_5\}$: 1, 2, 3; $\{V_2, V_5\}$: all; $\{V_4\}$: 1, 3, 4; $\{V_6\}$: 2; $\{V_4, V_6\}$: all; $\{V_7\}$: 2

The d-separation criterion

Definition:

Let $G = (V_G, A_G)$ be an acyclic directed graph. Let $X, Y, Z \subseteq V_G$ be sets of nodes in G .

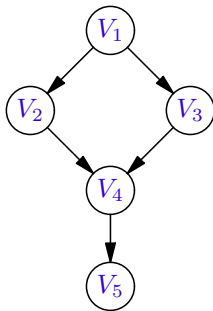
The set Z **d-separates** X from Y in G —notation: $\langle X \mid Z \mid Y \rangle_G^d$ —if *every simple chain* in G from a node in X to a node in Y is blocked by Z .

Remarks:

- The above notion is known as the **d-separation criterion**;
- $\langle X \mid \emptyset \mid Y \rangle_G^d$ indicates that all chains between X and Y , if any, contain a **head-to-head** node;
- if X and Y are **not** d-separated by Z , we say that they are **d-connected** given Z ; the chain(s) between X and Y that are not blocked are said to be **active** given Z .

An example

Consider the following DAG and d-separation statements:



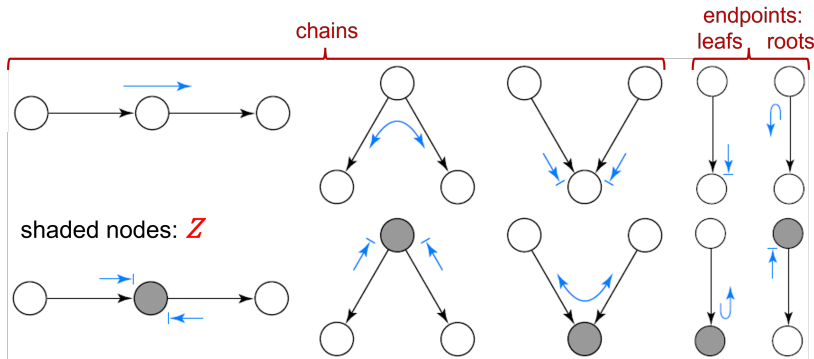
- a) $\langle \{V_1\} \mid \{V_2, V_3\} \mid \{V_5\} \rangle_G^d$
- b) $\langle \{V_1\} \mid \{V_4\} \mid \{V_5\} \rangle_G^d$
- c) $\langle \{V_2\} \mid \{V_1\} \mid \{V_3\} \rangle_G^d$
- d) $\langle \{V_2\} \mid \{V_1, V_5\} \mid \{V_3\} \rangle_G^d$
- e) $\langle \{V_2\} \mid \emptyset \mid \{V_3\} \rangle_G^d$
- f) $\langle \{V_1\} \mid \{V_3, V_4\} \mid \{V_2\} \rangle_G^d$

Which d-separation statements are valid in the graph ?

Answer: a,b,c

Bayes-Ball for determining d-separation

$\langle X | Z | Y \rangle_G^d$? Drop **bouncing balls** at X , which bounce from node to node along chains, using the 10 rules of Bayes-ball:



- balls quit a chain at a stop \rightarrow
- any node reached (**visited**) by a ball is on an active chain
- Y consists of all non-visited nodes

Independence relations and directed graphs

Definition:

Let I_{Pr} be an independence relation on a set of random variables V .

Let $G = (V_G, A_G)$ be an acyclic directed graph with $V_G = V$.

- graph G is called a **dependency map (D-map)** for I_{Pr} if for every $X, Y, Z \subseteq V$ we have that:

$$\text{if } I_{Pr}(X, Z, Y) \text{ then } \langle X | Z | Y \rangle_G^d;$$

- graph G is called an **independency map (I-map)** for I_{Pr} if for every $X, Y, Z \subseteq V$ we have that:

$$\text{if } \langle X | Z | Y \rangle_G^d \text{ then } I_{Pr}(X, Z, Y);$$

- graph G is called a **perfect map (P-map)** for I_{Pr} if G is both a D-map and an I-map for I_{Pr} .

Directed D-maps: what can they tell?

Let I_{Pr} be an independence relation and G a DAG.

Consider a D-map for I_{Pr} , then

V_1 and V_2 neighbours³ $\implies V_1, V_2$ **dependent**

V_1 and V_2 **non-neighbours** \implies **??** V_1 and V_2 can be:
dependent,
independent,
conditionally dependent, or
conditionally independent

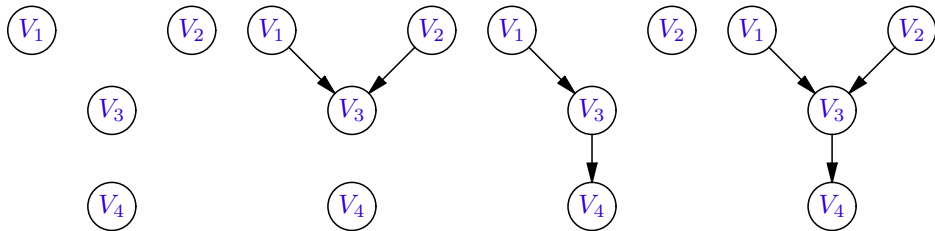
³i.e. directly connected by an arc

An example

Consider the independence relation I_{Pr} on $V = \{V_1, \dots, V_4\}$ defined by

$$I_{Pr}(\{V_1\}, \emptyset, \{V_2\}) \text{ and } I_{Pr}(\{V_1, V_2\}, \{V_3\}, \{V_4\})$$

Which of the following DAGs are D-maps for I_{Pr} ?



See Exercise 3.8 (Syllabus) Answer: all

Directed I-maps: what can they tell ?

Let I_{Pr} be an independence relation and G a DAG.

Consider an I-map for I_{Pr} , then

V_1 and V_2 non-neighbours $\implies V_1, V_2$ (cond.) independent,
or possibly(!) induced:
conditionally dependent

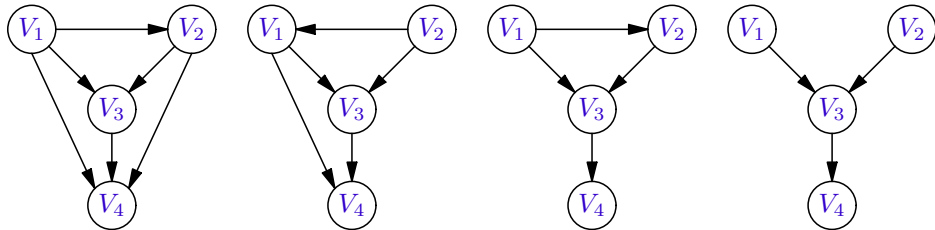
V_1 and V_2 neighbours \implies ?? V_1 and V_2 can be:
dependent,
independent,
conditionally dependent, or
conditionally independent

An example

Consider the independence relation I_{Pr} on $V = \{V_1, \dots, V_4\}$ defined by

$$I_{Pr}(\{V_1\}, \emptyset, \{V_2\}) \text{ and } I_{Pr}(\{V_1, V_2\}, \{V_3\}, \{V_4\})$$

Which of the following DAGs are I-maps for I_{Pr} ?



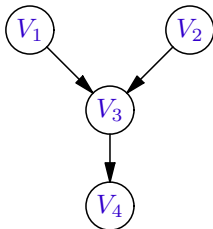
(See Exercise 3.8) Answer: all

An example

Consider the independence relation I_{Pr} on $V = \{V_1, \dots, V_4\}$ defined by

$$I_{Pr}(\{V_1\}, \emptyset, \{V_2\}) \text{ and } I_{Pr}(\{V_1, V_2\}, \{V_3\}, \{V_4\})$$

The following DAG is a perfect map for I_{Pr} :



Is this P-map for I_{Pr} **unique** ?

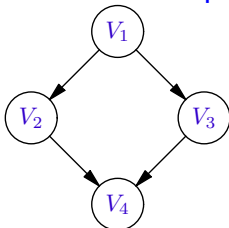
yes

An example

Consider the independence relation I_{Pr} on $V = \{V_1, \dots, V_4\}$ defined by

$$I_{Pr}(\{V_1\}, \{V_2, V_3\}, \{V_4\}) \text{ and } I_{Pr}(\{V_2\}, \{V_1, V_4\}, \{V_3\})$$

The relation I_{Pr} has an undirected P-map, but does not have a directed P-map. Consider for example the following DAG G :

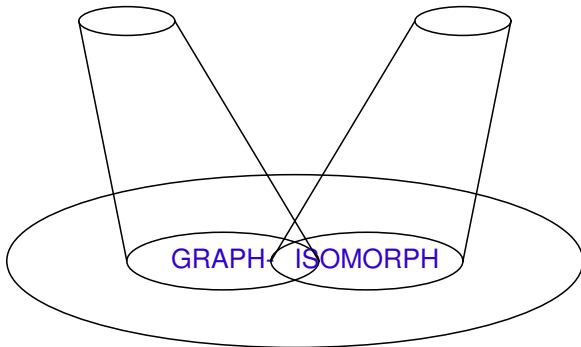


In graph G we have that $\langle \{V_1\} \mid \{V_2, V_3\} \mid \{V_4\} \rangle_G^d$, but also that $\langle \{V_2\} \mid \{V_1\} \mid \{V_3\} \rangle_G^d$!

Independence relations and their graphical representation

directed acyclic
graphs

undirected
graphs



independence relations

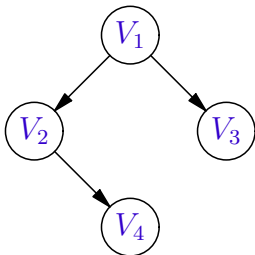
(Graph-isomorph: independence relation with perfect map.)

An I-map or a D-map ?

Reconsider the independence relation I_{Pr} on $V = \{V_1, \dots, V_4\}$ defined by

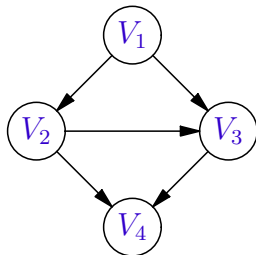
$$I_{Pr}(\{V_1\}, \{V_2, V_3\}, \{V_4\}) \text{ and } I_{Pr}(\{V_2\}, \{V_1, V_4\}, \{V_3\})$$

Compare the following two representations of independence relation I_{Pr} :



a D-map

and



an I-map

Recall what we were looking for...

- We can factorise any joint distribution using the **chain rule**:

$$\Pr(\mathbf{V}) = \Pr(V_n | V_{n-1} \wedge \dots \wedge V_1) \cdot \dots \cdot \Pr(V_2 | V_1) \cdot \Pr(V_1)$$

- We want to exploit I_{\Pr} to factorise the joint more efficiently \rightarrow store (conditional) distributions involving less variables:

$$\Pr(\mathbf{V}) \stackrel{?}{=} \Pr(V_n | V_m \wedge \dots \wedge V_k) \cdot \dots \cdot \Pr(V_2) \cdot \Pr(V_1)$$

BUT:

- $\Pr(X | Y) = \Pr(X)$ is mathematically correct **only** if X is truly independent of Y

A minimal I-map

Definition: Let I_{P_r} be an independence relation on a set of random variables V . Let $G = (V_G, A_G)$ be a graph with $V_G = V$.

The graph G is called a **minimal I-map** for I_{P_r} if the following conditions hold:

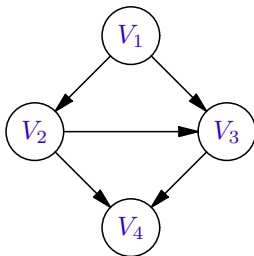
- G is an I-map for I_{P_r} , and
- no proper subgraph of G is an I-map for I_{P_r} .

An example

Consider the independence relation I_{Pr} on $V = \{V_1, \dots, V_4\}$ defined by

$$I_{Pr}(\{V_1\}, \{V_2, V_3\}, \{V_4\}) \text{ and } I_{Pr}(\{V_2\}, \{V_1, V_4\}, \{V_3\})$$

The following DAG is a **minimal** I-map for I_{Pr} :



Is this minimal I-map for I_{Pr} **unique** ?

no

Directed or undirected ? (I)

Directed and undirected I-maps are related.

Definition: The **moral graph** of a DAG $G = (V_G, A_G)$ is the undirected graph obtained as follows:

- for each $V_k \in V_G$ add an edge between each pair of unconnected parents $V_i, V_j \in \rho_G(V_k)$;
- drop the directions of all arcs.

Definition: A graph is **triangulated** or **chordal** if any loop of length ≥ 4 contains a shortcut.

Proposition: Let I be an independence relation over V . Consider graphs $G = (V_G, A_G)$ and $G' = (V, E_{G'})$. Then,

G is an I-map for I $\xrightleftharpoons[\text{triangulation+add direction}]{\text{moralisation+drop direction}}$ G' is an I-map for I

Directed or undirected ? (II)

Consider the following properties (partly proven later):

- Let G be a directed acyclic graph. Then G is a directed I-map of $I_{Pr} \iff Pr$ can be written as

$$Pr(\mathbf{V}) = \prod_{V_i} Pr(V_i \mid \rho_G(V_i))$$

- Let G be an undirected graph. Then G is an undirected I-map of $I_{Pr} \iff$ ⁴ Pr can be written as

$$Pr(\mathbf{V}) = K \cdot \prod_{C_i} \Phi(C_i)$$

← what's the meaning of these clique potentials!?

for some normalisation factor K .

⁴ \implies requires Pr to be strictly positive