

week 11 day 1

Graphical models: continuation
Algebraic & Geometric Methods in Statistics

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Created for Math/Stat 561

Mar 22, 2023.

Material

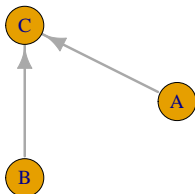
- Chapter 13: Graphical models
- We are following after Miles Bakenhus' course project lecture on sections 13.1 and 13.2.
- We will review a couple of examples from the basics of graphical models (think of the first st of these slides as your study worksheet in class).
- We will then see a few more examples
- Discuss the *discrete distributions* and connection to algebra&geometry.

Examples

- Genes:
 - three genes in this example A,B,C
- Relationships:
 - A regulates C
 - B regulates C

BIOLOGY

- genes
- relationships



GRAPH

- vertices
- edges

$$P(A, B, C) = P(A)P(B)P(C|A, B)$$

PROBABILISTIC MODEL

- random variables
- statistical dependencies

Correlation vs causation

- Genes regulated as $X \rightarrow Y \rightarrow Z$
- Z and X are correlated, but do not interact directly

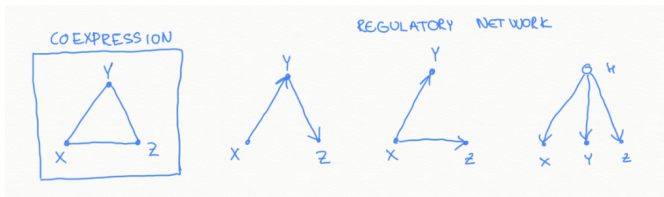


Figure 1: Source: K. Kubjas

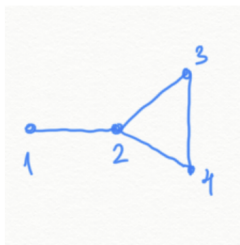
Separator

Poll:

Let G be a graph with nodes $\{1,2,3,4\}$ and edges $(1,2)$, $(2,3)$, $(2,4)$, $(3,4)$.

Which of the following sets are separators for the nodes 1 and 4?

- 1 $\{2\}$
- 2 $\{3\}$
- 3 $\{2,3\}$
- 4 $\{1,2,3,4\}$



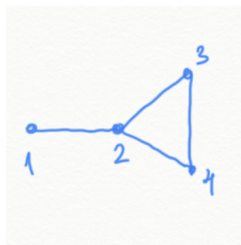
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Answer

Correct answers: 1. and 3.

Reminder: conditional independence definition

[board]

Pairwise Markov property

Let $G = (V, E)$ be an undirected graph.

Definition

The **pairwise Markov property associated to G** consists of all conditional independence statements

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Pairwise Markov property

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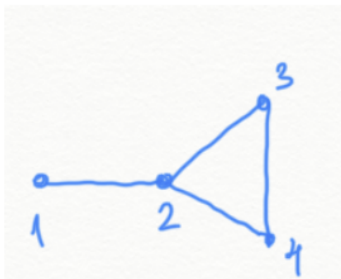
Definition

The **pairwise Markov property associated to G** consists of all conditional independence statements $X_u \perp\!\!\!\perp X_v | X_{V(G) \setminus \{u,v\}}$, where (u, v) is not an edge of G .

Question (example)

The pairwise Markov property associated to G below is:

- 1 $\{1 \perp\!\!\!\perp 3 | (2, 4), 1 \perp\!\!\!\perp 4 | (2, 3)\}$
- 2 $\{1 \perp\!\!\!\perp 3 | 2, 1 \perp\!\!\!\perp 4 | 2\}$
- 3 $\{1 \perp\!\!\!\perp 3 | (2, 4)\}$
- 4 $\{1 \perp\!\!\!\perp 4 | (2, 3)\}$



Pairwise Markov property

Let $G = (V, E)$ be an undirected graph.

Definition

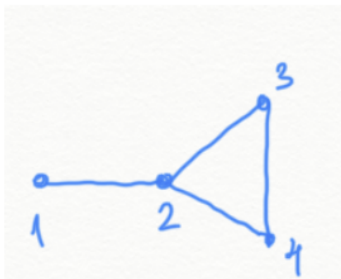
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Correct answer: 1.



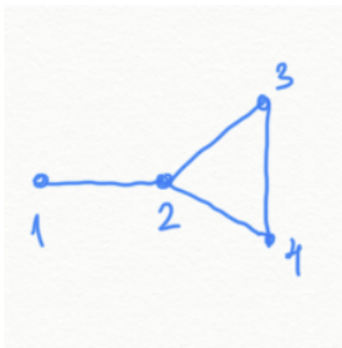
Multivariate Gaussian random variables

- The CI statement $X_u \perp\!\!\!\perp X_v | X_{V \setminus \{u,v\}}$ is equivalent to the matrix $\Sigma_{V \setminus \{u\}, V \setminus \{v\}}$ having rank $|V \setminus \{u, v\}|$, or equivalently $\det(\Sigma_{V \setminus \{u\}, V \setminus \{v\}}) = 0$.
- This is equivalent to $(\Sigma^{-1})_{u,v} = 0$.
- The pairwise Markov property holds for a Gaussian distribution if and only if the entries of the concentration matrix corresponding to non-edges are zero.

Question (example)

What is the form of the concentration matrices of a Gaussian distribution obeying the pairwise Markov property have?

$$\begin{matrix} \textcircled{1} \\ \textcircled{2} \end{matrix} \begin{bmatrix} k_{11} & 0 & k_{13} & k_{14} \\ 0 & k_{22} & 0 & 0 \\ k_{13} & 0 & k_{33} & 0 \\ k_{14} & 0 & 0 & k_{44} \\ k_{11} & k_{12} & 0 & 0 \\ k_{12} & k_{22} & k_{23} & k_{24} \\ 0 & k_{23} & k_{33} & k_{34} \\ 0 & k_{24} & k_{34} & k_{44} \end{bmatrix}$$

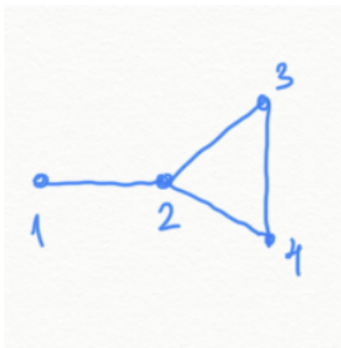


Question (example)

What is the form of the concentration matrices of a Gaussian distribution obeying the pairwise Markov property have?

- 1
$$\begin{bmatrix} k_{11} & 0 & k_{13} & k_{14} \\ 0 & k_{22} & 0 & 0 \\ k_{13} & 0 & k_{33} & 0 \\ k_{14} & 0 & 0 & k_{44} \end{bmatrix}$$
- 2
$$\begin{bmatrix} k_{11} & k_{12} & 0 & 0 \\ k_{12} & k_{22} & k_{23} & k_{24} \\ 0 & k_{23} & k_{33} & k_{34} \\ 0 & k_{24} & k_{34} & k_{44} \end{bmatrix}$$

Correct answer: 2.



Global Markov property

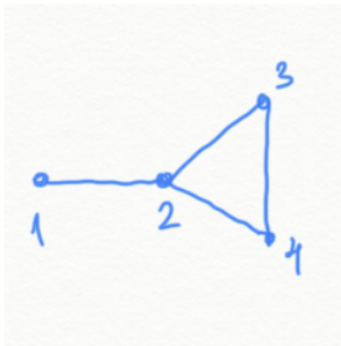
Definition (reminder!)

[board]

Question (example)

The global Markov property associated to G is:

- ① $\{1 \perp\!\!\!\perp (3, 4) | 2\}$
- ② $\{1 \perp\!\!\!\perp 3 | (2, 4), \quad 1 \perp\!\!\!\perp 4 | (2, 3)\}$
- ③ $\{1 \perp\!\!\!\perp 3 | (2, 4), \quad 1 \perp\!\!\!\perp 4 | (2, 3),$
 $1 \perp\!\!\!\perp (3, 4) | 2\}$



Global Markov property

Definition (reminder!)

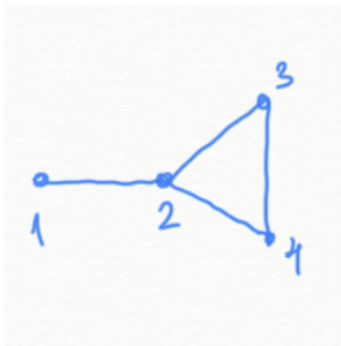
[board]

Question (example)

The global Markov property associated to G is:

- 1 $\{1 \perp\!\!\!\perp (3, 4) | 2\}$
- 2 $\{1 \perp\!\!\!\perp 3 | (2, 4), \quad 1 \perp\!\!\!\perp 4 | (2, 3)\}$
- 3 $\{1 \perp\!\!\!\perp 3 | (2, 4), \quad 1 \perp\!\!\!\perp 4 | (2, 3),$
 $1 \perp\!\!\!\perp (3, 4) | 2\}$

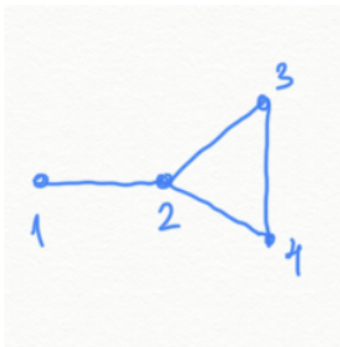
Correct answer: 3.



Markov properties

In the last lecture, Miles showed that pairwise Markov statements C_{pairs} are a subset of Global statements C_{global} .

- In our example:
- $C_{pairs} = \{1 \perp\!\!\!\perp 3 | (2, 4), 1 \perp\!\!\!\perp 4 | (2, 3)\}$.
- $C_{global} = C_{pairs} \cup \{1 \perp\!\!\!\perp (3, 4) | 2\}$.



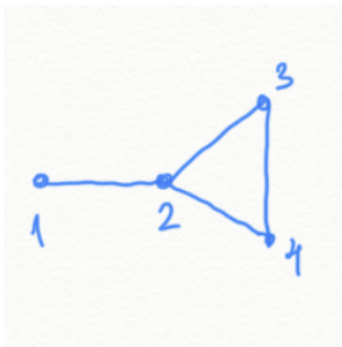
Factorization property

- We want to characterize **all** the distributions that satisfy the Markov properties for a *given graph*.
 - Hammersley-Clifford theorem relates the implicit description of a graphical model through Markov properties to a parametric description.
- Recall: definition of factorizing according to a graph via cliques.
[board]
- Review Theorem 13.2.10 (recursive factorization in DAGs) with *proof*.

Question (example)

What are the **maximal cliques** of G ?

- ① $\{1\}$
- ② $\{1, 2\}$
- ③ $\{1, 2, 3, \}$
- ④ $\{2, 3, 4\}$

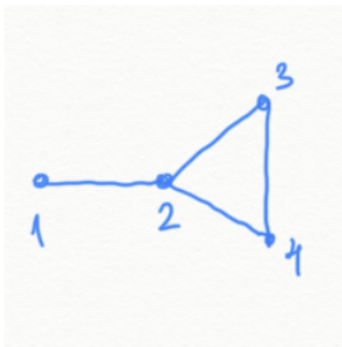


Question (example)

What are the **maximal cliques** of G ?

- ① $\{1\}$
- ② $\{1, 2\}$
- ③ $\{1, 2, 3, \}$
- ④ $\{2, 3, 4\}$

Correct answers: 2 and 4.



Examples from 13.4

- (Homogeneous) Markov chain - example 13.4.1 and connection to chapter 1
- Hidden Markov model

[board notes]

Discrete distributions - and algebra&geometry

- $X = \{X_1, \dots, X_m\}$ discrete random vector
- The distribution p on X factors according to G if

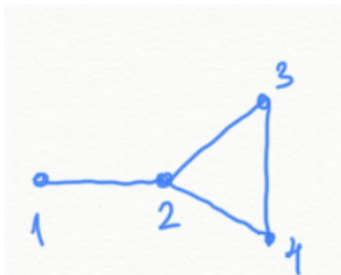
$$p_{i_1 i_2 \dots i_m} \propto \prod_{C \in \mathcal{C}(G)} \theta_{i_C}^{(C)}.$$

- This is a **monomial parametrization**. Hence the set of distributions that factorize according to a graph G form a hierarchical **log-linear model**.

$$C_{pairs} = \{1 \perp\!\!\!\perp 3 | (2, 4), 1 \perp\!\!\!\perp 4 | (2, 3)\}.$$
$$C_{global} = C_{pairs} \cup \{1 \perp\!\!\!\perp (3, 4) | 2\}.$$

- Spell this out: [board]

$$p(x) = \frac{1}{Z} \theta_{i_1 i_2}^{(12)} \theta_{i_2 i_3 i_4}^{(234)}.$$



Pairwise Markov propriety - algebra

$$C_{pairs} = \{1 \perp\!\!\!\perp 3 | (2, 4), 1 \perp\!\!\!\perp 4 | (2, 3)\}$$

Question (example)

How many polynomials generate the corresponding CI ideal?

Pairwise Markov property - algebra

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Question (example)

How many polynomials generate the corresponding CI ideal?

- $M_1 = \begin{bmatrix} p_{0000} & p_{0001} & p_{0010} & p_{0011} \\ p_{1000} & p_{1001} & p_{1010} & p_{1011} \end{bmatrix}$
- $M_2 = \begin{bmatrix} p_{0100} & p_{0101} & p_{0110} & p_{0111} \\ p_{1100} & p_{1101} & p_{1110} & p_{1111} \end{bmatrix}$

Pairwise Markov property - algebra

$$C_{pairs} = \{1 \perp\!\!\!\perp 3 | (2, 4), 1 \perp\!\!\!\perp 4 | (2, 3)\}$$

Question (example)

How many polynomials generate the corresponding CI ideal?

- $M_1 = \begin{bmatrix} p_{0000} & p_{0001} & p_{0010} & p_{0011} \\ p_{1000} & p_{1001} & p_{1010} & p_{1011} \end{bmatrix}$
- $M_2 = \begin{bmatrix} p_{0100} & p_{0101} & p_{0110} & p_{0111} \\ p_{1100} & p_{1101} & p_{1110} & p_{1111} \end{bmatrix}$
- The conditional independence ideal for each statement is generated by two minors of M_1 and two minors of M_2

```

i1 : R1 = QQ[p_(0,0,0,0)..p_(1,1,1,1)]
o1 = R1
o1 : PolynomialRing

i2 : M1 = matrix{{p_(0,0,0,0),p_(0,0,0,1),p_(0,0,1,0),p_(0,0,1,1)},{p_(1,0,0,0),p_(1,0,0,1),p_(1,0,1,0),p_(1,0,1,1)}}
o2 = | p_(0,0,0,0) p_(0,0,0,1) p_(0,0,1,0) p_(0,0,1,1) |
      | p_(1,0,0,0) p_(1,0,0,1) p_(1,0,1,0) p_(1,0,1,1) |
o2 : Matrix R1 ← R1

i3 : M2 = matrix{{p_(0,1,0,0),p_(0,1,0,1),p_(0,1,1,0),p_(0,1,1,1)},{p_(1,1,0,0),p_(1,1,0,1),p_(1,1,1,0),p_(1,1,1,1)}}
o3 = | p_(0,1,0,0) p_(0,1,0,1) p_(0,1,1,0) p_(0,1,1,1) |
      | p_(1,1,0,0) p_(1,1,0,1) p_(1,1,1,0) p_(1,1,1,1) |
o3 : Matrix R1 ← R1

i4 : IP = ideal(det(M1_{0,2}),det(M1_{1,3}),det(M2_{0,2}),det(M2_{1,3}),det(M1_{0,1}),det(M1_{2,3}),det(M2_{0,1}),det(M2_{2,3}))
o4 = ideal (- p
            0,0,1,0 1,0,0,0 + p
            0,0,0,0 1,0,1,0 , - p
            0,0,1,1 1,0,0,1 +
            -----
            p
            0,0,0,1 1,0,1,1 , - p
            0,1,1,0 1,1,0,0 + p
            0,1,0,0 1,1,1,0 , -
            -----
            p
            0,1,1,1 1,1,0,1 + p
            0,1,0,1 1,1,1,1 , - p
            0,0,0,1 1,0,0,0 +
            -----
            p
            0,0,0,0 1,0,0,1 , - p
            0,0,1,1 1,0,1,0 + p
            0,0,1,0 1,0,1,1 , -
            -----
            p
            0,1,0,1 1,1,0,0 + p
            0,1,0,0 1,1,0,1 , - p
            0,1,1,1 1,1,1,0 +
            -----
            p
            0,1,1,0 1,1,1,1 )
o4 : Ideal of R1

```

Figure 2: code will be shared after class

Global Markov property - algebra

$$C_{global} = C_{pairs} \cup \{1 \perp\!\!\!\perp (3, 4) | 2\}.$$

- $M_1 = \begin{bmatrix} p_{0000} & p_{0001} & p_{0010} & p_{0011} \\ p_{1000} & p_{1001} & p_{1010} & p_{1011} \end{bmatrix}$

- $M_2 = \begin{bmatrix} p_{0100} & p_{0101} & p_{0110} & p_{0111} \\ p_{1100} & p_{1101} & p_{1110} & p_{1111} \end{bmatrix}$

- The conditional independence ideal for each statement is generated by **all** 2×2 minors M_1 and of M_2

Recall slide 8-9 of Lecture 4!

Factorization according to G - algebra

$$p_{i_1 i_2 \dots i_m} = \frac{1}{Z} \prod_{C \in \mathcal{C}(G)} \theta_{i_C}^{(C)}.$$

Question (example)

How many parameters does this parametrization map have?

Factorization according to G - algebra

$$p_{i_1 i_2 \dots i_m} = \frac{1}{Z} \prod_{C \in \mathcal{C}(G)} \theta_{i_C}^{(C)}.$$

Question (example)

How many parameters does this parametrization map have?

$$p_{ijkl} = a_{ij} b_{jkl}$$

- We can compute the ideal of this model I_G as follows.

It feels like this will be week 11, day 2. :)

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This document is created for Math/Stat 561, Spring 2023.

The slides that are not directly from the book are sourced from **Kaie Kubjas'** Algebraic Statistics course at Aalto University.

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