

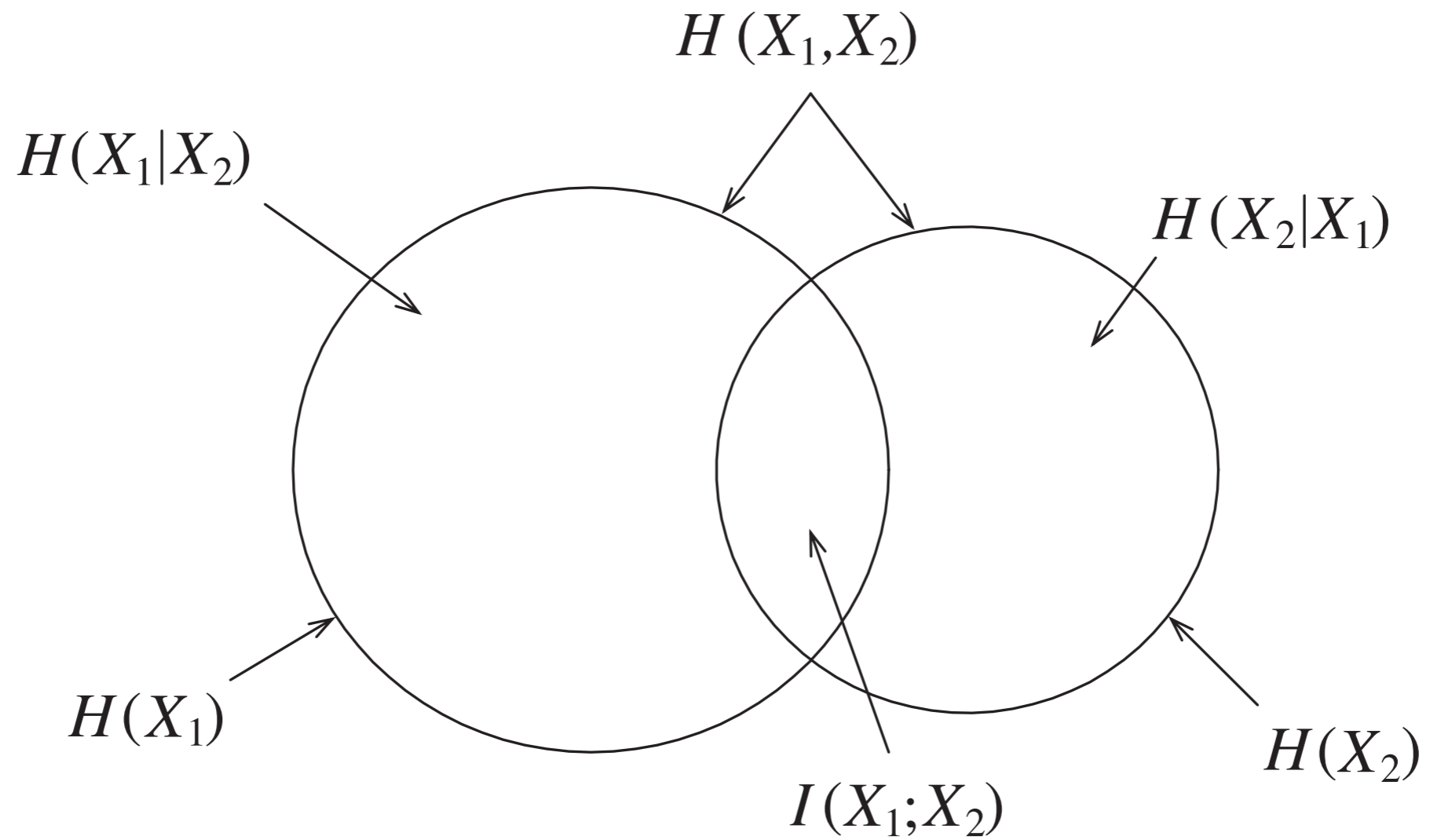
# Chapter 3

## The $I$ -Measure

© Raymond W. Yeung 2010

Department of Information Engineering  
The Chinese University of Hong Kong

# An Example



# Substitution of Symbols

$$\begin{array}{rcl} H/I & \leftrightarrow & \mu^* \\ , & \leftrightarrow & \cup \\ ; & \leftrightarrow & \cap \\ | & \leftrightarrow & - \end{array}$$

- $\mu^*$  is some signed measure on  $\mathcal{F}_n$ .
- Examples:
  - 1.

$$\begin{aligned} \mu^*(\tilde{X}_1 - \tilde{X}_2) &= H(X_1|X_2) \\ \mu^*(\tilde{X}_2 - \tilde{X}_1) &= H(X_2|X_1), \\ \mu^*(\tilde{X}_1 \cap \tilde{X}_2) &= I(X_1; X_2) \end{aligned}$$

## 2. Inclusion-Exclusion formulation in set-theory

$$\mu^*(\tilde{X}_1 \cup \tilde{X}_2) = \mu^*(\tilde{X}_1) + \mu^*(\tilde{X}_2) - \mu^*(\tilde{X}_1 \cap \tilde{X}_2)$$

corresponds to

$$H(X_1, X_2) = H(X_1) + H(X_2) - I(X_1; X_2)$$

in information theory.

# 3.1 Preliminaries

**Definition 3.1** The **field**  $\mathcal{F}_n$  generated by sets  $\tilde{X}_1, \tilde{X}_2, \dots, \tilde{X}_n$  is the collection of sets which can be obtained by any sequence of usual set operations (union, intersection, complement, and difference) on  $\tilde{X}_1, \tilde{X}_2, \dots, \tilde{X}_n$ .

**Definition 3.2** The **atoms** of  $\mathcal{F}_n$  are sets of the form  $\bigcap_{i=1}^n Y_i$ , where  $Y_i$  is either  $\tilde{X}_i$  or  $\tilde{X}_i^c$ , the complement of  $\tilde{X}_i$ .

## Example 3.3

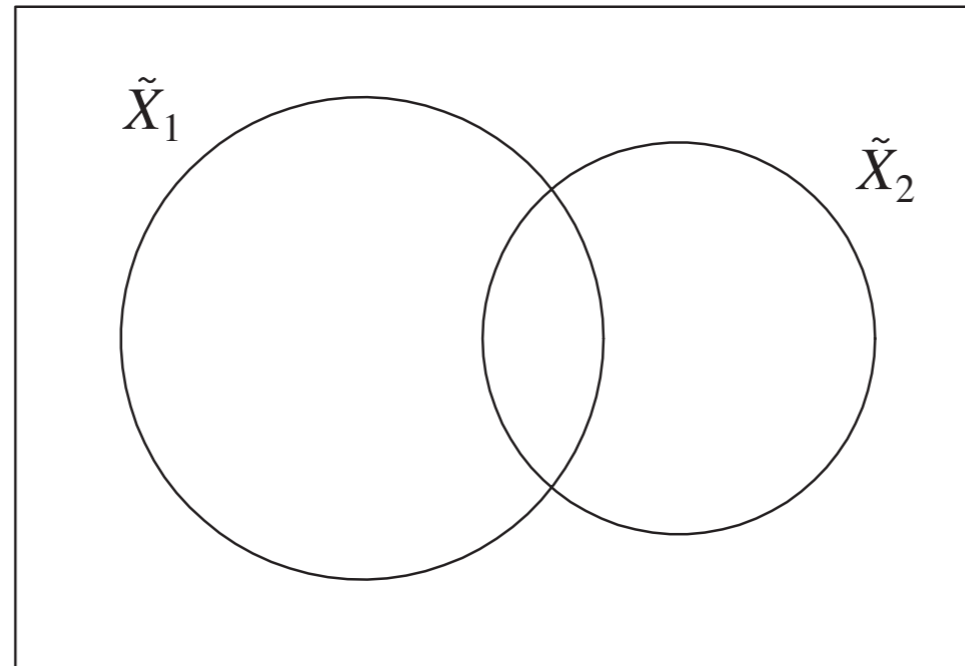
- The sets  $\tilde{X}_1$  and  $\tilde{X}_2$  generate the field  $\mathcal{F}_2$ .
- There are 4 atoms in  $\mathcal{F}_2$ .
- There are a total of 16 sets in  $\mathcal{F}_2$

**Definition 3.4** A real function  $\mu$  defined on  $\mathcal{F}_n$  is called a **signed measure** if it is **set-additive**, i.e., for disjoint  $A$  and  $B$  in  $\mathcal{F}_n$ ,

$$\mu(A \cup B) = \mu(A) + \mu(B).$$

**Remark**  $\mu(\emptyset) = 0$ .

# Example 3.5



- A signed measure  $\mu$  on  $\mathcal{F}_2$  is completely specified by the values on the atoms

$$\mu(\tilde{X}_1 \cap \tilde{X}_2), \mu(\tilde{X}_1^c \cap \tilde{X}_2), \mu(\tilde{X}_1 \cap \tilde{X}_2^c), \mu(\tilde{X}_1^c \cap \tilde{X}_2^c)$$

- The value of  $\mu$  on other sets in  $\mathcal{F}_2$  are obtained by set-additivity.

# Section 3.3

## Construction of the $I$ -Measure $\mu^*$

- Let  $\tilde{X}$  be a set corresponding to a r.v.  $X$ .
- $\mathcal{N}_n = \{1, 2, \dots, n\}$ .
- Universal set

$$\Omega = \bigcup_{i \in \mathcal{N}_n} \tilde{X}_i.$$

- Empty atom of  $\mathcal{F}_n$

$$A_0 = \bigcap_{i \in \mathcal{N}_n} \tilde{X}_i^c$$

- $\mathcal{A}$  is the set of other atoms of  $\mathcal{F}_n$ , called non-empty atoms.  $|\mathcal{A}| = 2^n - 1$ .
- A signed measure  $\mu$  on  $\mathcal{F}_n$  is completely specified by the values of  $\mu$  on the nonempty atoms of  $\mathcal{F}_n$ .



**Notations** For nonempty subset  $G$  of  $\mathcal{N}_n$ :

- $X_G = (X_i, i \in G)$
- $\tilde{X}_G = \cup_{i \in G} \tilde{X}_i$

**Theorem 3.6** Let

$$\mathcal{B} = \left\{ \tilde{X}_G : G \text{ is a nonempty subset of } \mathcal{N}_n \right\}.$$

Then a signed measure  $\mu$  on  $\mathcal{F}_n$  is completely specified by  $\{\mu(B), B \in \mathcal{B}\}$ , which can be any set of real numbers.

# Proof of Theorem 3.6

- $|\mathcal{A}| = |\mathcal{B}| = 2^n - 1$
- $\mathbf{u}$  – column  $k$ -vector of  $\mu(A)$ ,  $A \in \mathcal{A}$
- $\mathbf{h}$  – column  $k$ -vector of  $\mu(B)$ ,  $B \in \mathcal{B}$
- Obviously can write  $\mathbf{h} = C_n \mathbf{u}$ , where  $C_n$  is a *unique*  $k \times k$  matrix.
- On the other hand, for each  $A \in \mathcal{A}$ ,  $\mu(A)$  can be expressed as a linear combination of  $\mu(B)$ ,  $B \in \mathcal{B}$  by applying

$$\begin{aligned}\mu(A \cap B - C) &= \mu(A - C) + \mu(B - C) - \mu(A \cup B - C) \\ \mu(A - B) &= \mu(A \cup B) - \mu(B).\end{aligned}$$

(see Appendix 3.A) That is,  $\mathbf{u} = D_n \mathbf{h}$ .

- Then  $\mathbf{u} = (D_n C_n) \mathbf{u}$ , showing that  $D_n = (C_n)^{-1}$  is unique.

# Two Lemmas

## Lemma 3.7

$$\mu(A \cap B - C) = \mu(A \cup C) + \mu(B \cup C) - \mu(A \cup B \cup C) - \mu(C).$$

## Lemma 3.8

$$I(X; Y|Z) = H(X, Z) + H(Y, Z) - H(X, Y, Z) - H(Z).$$

- Construct the  $I$ -Measure  $\mu^*$  on  $\mathcal{F}_n$  using by defining

$$\mu^*(\tilde{X}_G) = H(X_G)$$

for all nonempty subsets  $G$  of  $\mathcal{N}_n$ .

- $\mu^*$  is meaningful if it is consistent with all Shannon's information measures via the substitution of symbols, i.e., the following must hold for all (not necessarily disjoint) subsets  $G, G', G''$  of  $\mathcal{N}_n$  where  $G$  and  $G'$  are nonempty:

$$\mu^*(\tilde{X}_G \cap \tilde{X}_{G'} - \tilde{X}_{G''}) = I(X_G; X_{G'} | X_{G''})$$

- $G'' = \emptyset$

$$\mu^*(\tilde{X}_G \cap \tilde{X}_{G'}) = I(X_G; X_{G'})$$

$$\underline{G = G'}$$

$$\mu^*(\tilde{X}_G - \tilde{X}_{G''}) = H(X_G | X_{G''})$$

$$\underline{G = G' \text{ and } G'' = \emptyset}$$

$$\mu^*(\tilde{X}_G) = H(X_G)$$

**Theorem 3.9**  $\mu^*$  is the unique signed measure on  $\mathcal{F}_n$  which is consistent with all Shannon's information measures.

## Implications

- Can formally regard Shannon's information measures for  $n$  r.v.'s as the unique signed measure  $\mu^*$  defined on  $\mathcal{F}_n$ .
- Can employ set-theoretic tools to manipulate expressions of Shannon's information measures.

# Proof of Theorem 3.9

•

$$\begin{aligned} & \mu^*(\tilde{X}_G \cap \tilde{X}_{G'} - \tilde{X}_{G''}) \\ &= \mu^*(\tilde{X}_{G \cup G''}) + \mu^*(\tilde{X}_{G' \cup G''}) - \mu^*(\tilde{X}_{G \cup G' \cup G''}) - \mu^*(\tilde{X}_{G''}) \\ &= H(X_{G \cup G''}) + H(X_{G' \cup G''}) - H(X_{G \cup G' \cup G''}) - H(X_{G''}) \\ &= I(X_G; X_{G'} | X_{G''}), \end{aligned}$$

- In order that  $\mu^*$  is consistent with all Shannon's information measures,

$$\mu^*(\tilde{X}_G) = H(X_G)$$

for all nonempty subsets  $G$  of  $\mathcal{N}_n$ .

- Thus  $\mu^*$  is the unique signed measure on  $\mathcal{F}_n$  which is consistent with all Shannon's information measures.

## 3.4 $\mu^*$ can be Negative

- $\mu^*$  is nonnegative for  $n = 2$ .
- For  $n = 3$ ,  $\mu^*(\tilde{X}_1 \cap \tilde{X}_2 \cap \tilde{X}_3) = I(X_1; X_2; X_3)$  can be negative.

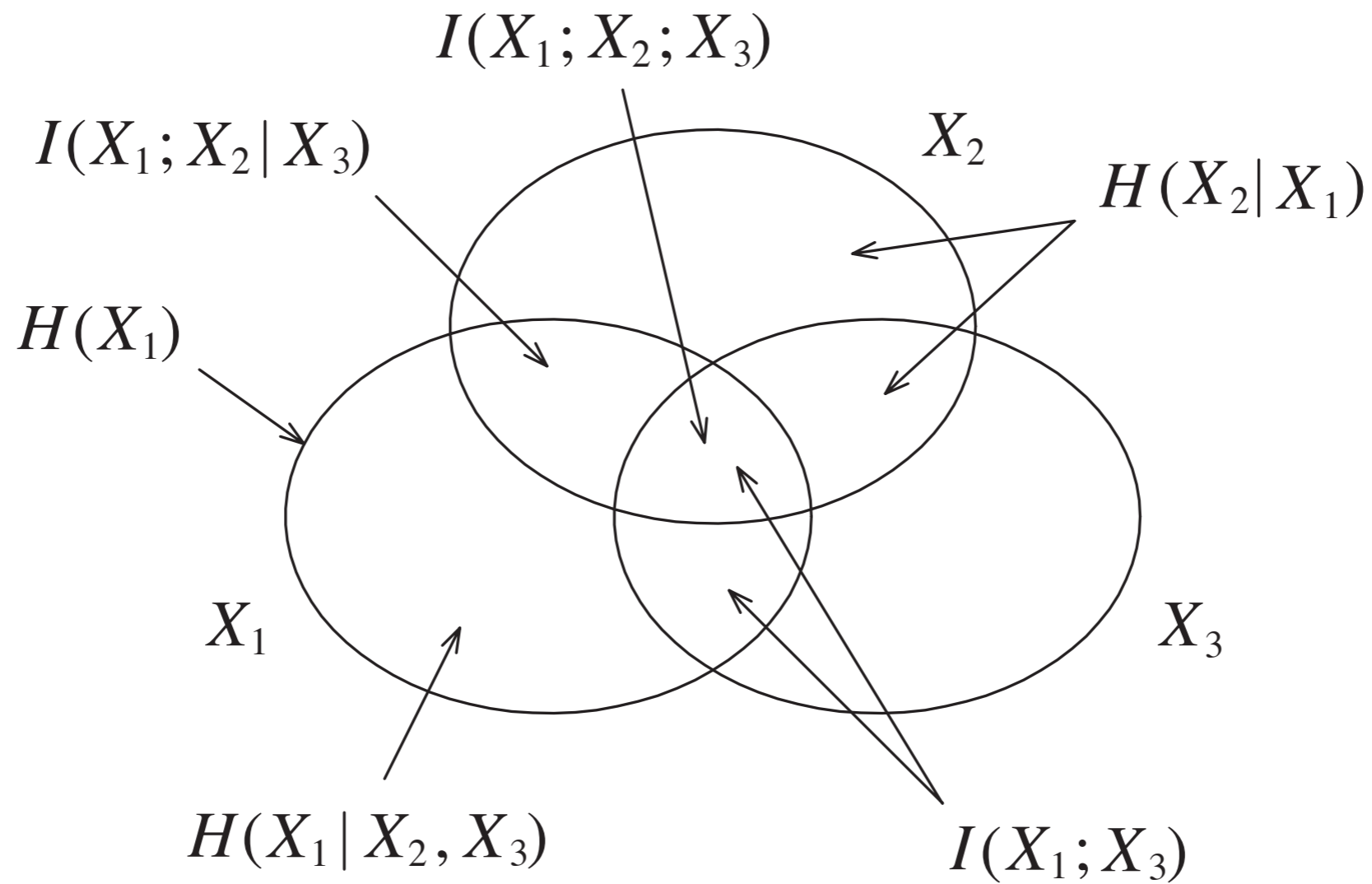
### Example 3.10

- $X_1, X_2$  – i.i.d. binary r.v.’s uniform on  $\{0, 1\}$
- $X_3 = X_1 + X_2 \pmod{2}$
- Easy to check:
  - $H(X_i) = 1$ , for all  $i$
  - $X_1, X_2, X_3$  are pairwise independent, so that

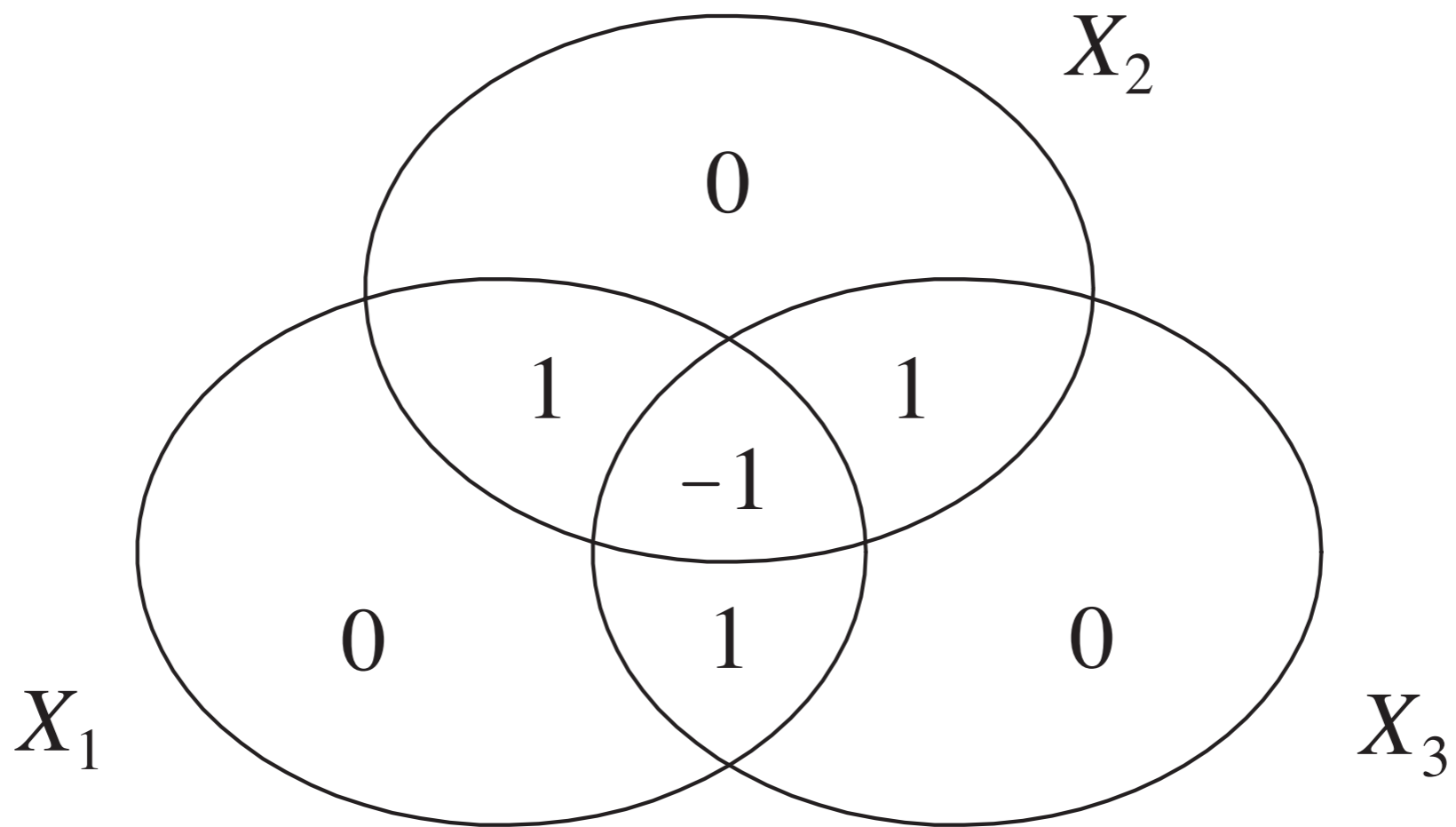
$$H(X_i, X_j) = 2 \text{ and } I(X_i; X_j) = 0, \text{ for all } i \neq j$$

- Under these constraints,  $I(X_1; X_2; X_3) = -1$ .

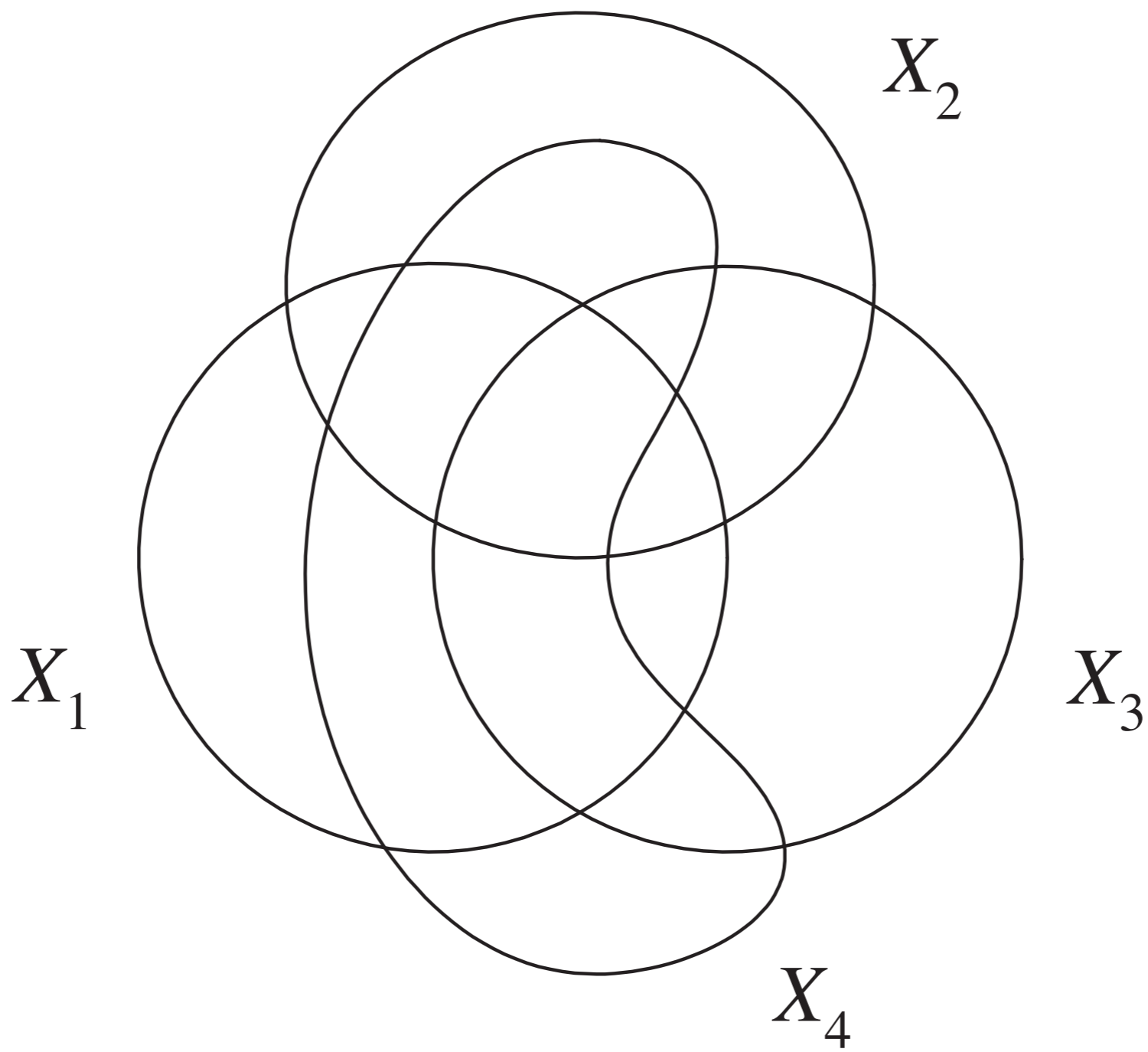
# 3.5 Information Diagrams







The information diagram for Example 3.10



**Theorem 3.11** If there is no constraint on  $X_1, X_2, \dots, X_n$ , then  $\mu^*$  can take any set of nonnegative values on the nonempty atoms of  $\mathcal{F}_n$ .

## Proof

- Let  $Y_A, A \in \mathcal{A}$  be mutually independent r.v.'s.
- Define  $X_i, i = 1, 2, \dots, n$  by

$$X_i = (Y_A : A \in \mathcal{A} \text{ and } A \subset \tilde{X}_i).$$

- Claim:  $X_1, X_2, \dots, X_n$  so constructed induce the  $I$ -Measure  $\mu^*$  such that

$$\mu^*(A) = H(Y_A), \text{ for all } A \in \mathcal{A}.$$

which are arbitrary nonnegative numbers.

- Consider

$$\begin{aligned}
H(X_G) &= H(X_i, i \in G) \\
&= H((Y_A : A \in \mathcal{A} \text{ and } A \subset \tilde{X}_i), i \in G) \\
&= H(Y_A : A \in \mathcal{A} \text{ and } A \subset \tilde{X}_G) \\
&= \sum_{A \in \mathcal{A}: A \subset \tilde{X}_G} H(Y_A)
\end{aligned}$$

- On the other hand,

$$H(X_G) = \mu^*(\tilde{X}_G) = \sum_{A \in \mathcal{A}: A \subset \tilde{X}_G} \mu^*(A)$$

- Thus

$$\sum_{A \in \mathcal{A}: A \subset \tilde{X}_G} H(Y_A) = \sum_{A \in \mathcal{A}: A \subset \tilde{X}_G} \mu^*(A)$$

- One solution is

$$\mu^*(A) = H(Y_A), \text{ for all } A \in \mathcal{A}.$$

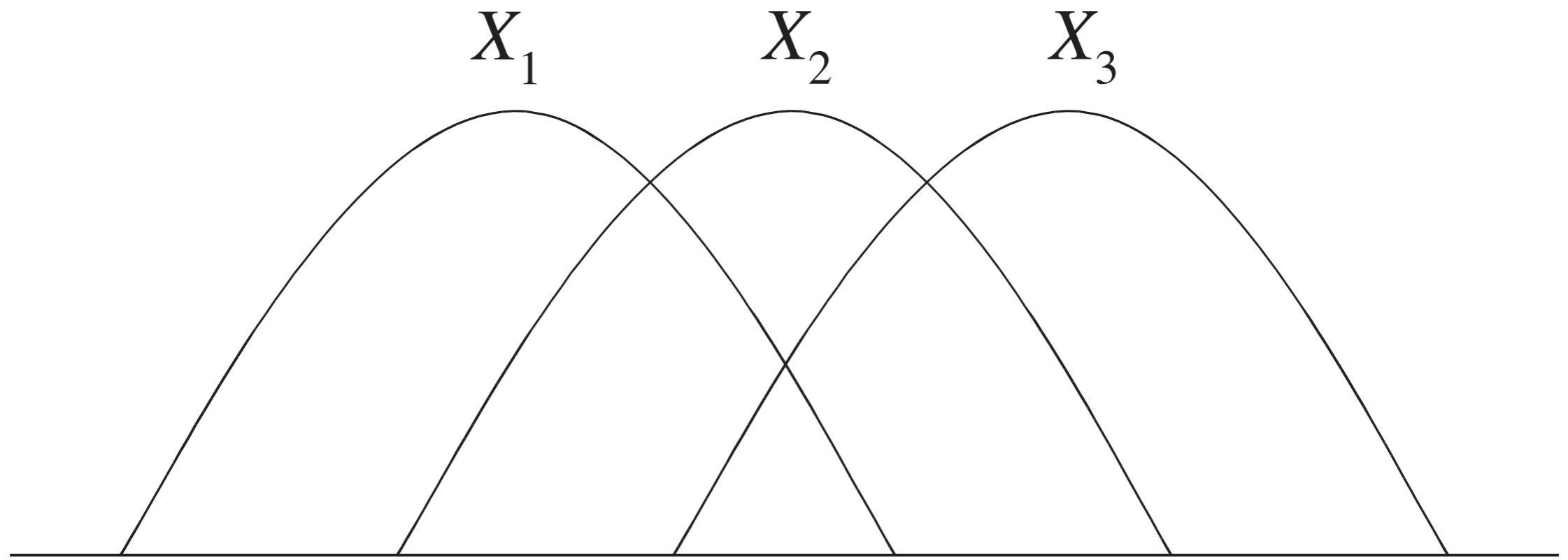
- By the uniqueness of  $\mu^*$ , this is the only solution.

# Information Diagrams for Markov Chains

- If  $X_1 \rightarrow X_2 \rightarrow \cdots \rightarrow X_n$  form a Markov chain, then the structure of  $\mu^*$  is much simpler and hence the information diagram can be simplified.
- For  $n = 3$ ,  $X_1 \rightarrow X_2 \rightarrow X_3$  iff  $I(X_1; X_3|X_2) = 0$ . So the atom  $\tilde{X}_1 \cap \tilde{X}_3 - \tilde{X}_2$  can be suppressed.
- The values of  $\mu^*$  on the remaining atoms correspond to Shannon's information measures and hence are nonnegative. In particular,

$$\mu^*(\tilde{X}_1; \tilde{X}_2; \tilde{X}_3) = \mu^*(\tilde{X}_1; \tilde{X}_3) = I(X_1; X_3)$$

- Thus,  $\mu^*$  is a measure.



- For  $n = 4$ ,  $\mu^*$  vanishes on the following atoms:

$$\tilde{X}_1 \cap \tilde{X}_2^c \cap \tilde{X}_3 \cap \tilde{X}_4^c$$

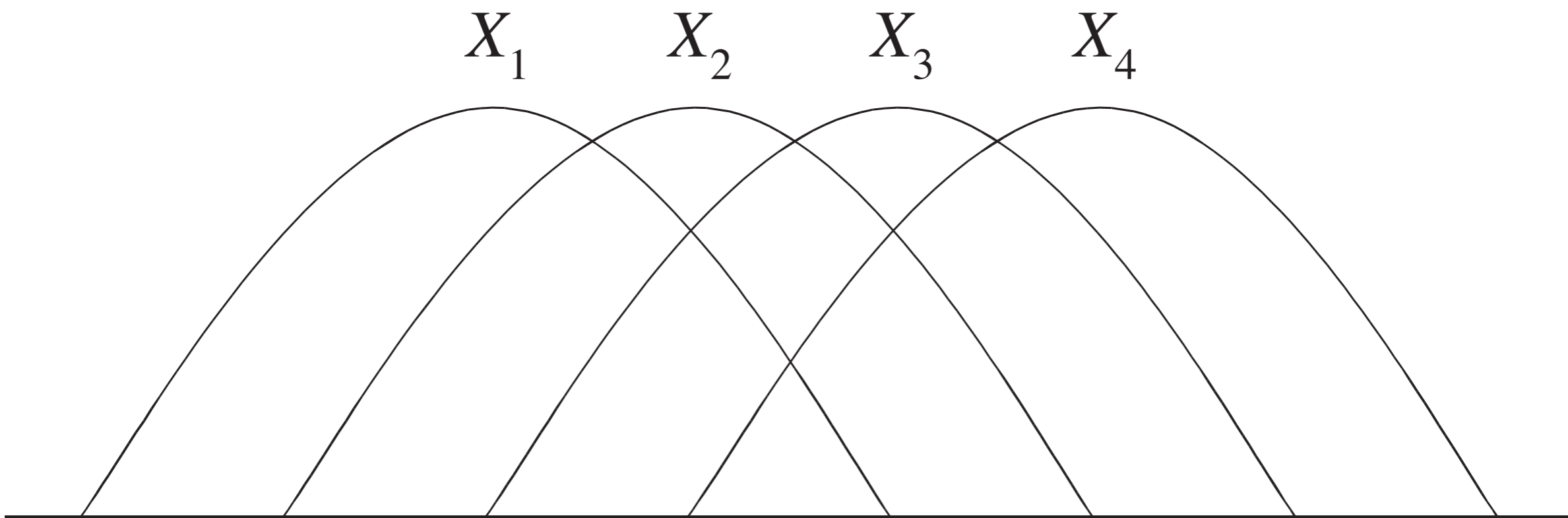
$$\tilde{X}_1 \cap \tilde{X}_2^c \cap \tilde{X}_3 \cap \tilde{X}_4$$

$$\tilde{X}_1 \cap \tilde{X}_2^c \cap \tilde{X}_3^c \cap \tilde{X}_4$$

$$\tilde{X}_1 \cap \tilde{X}_2 \cap \tilde{X}_3^c \cap \tilde{X}_4$$

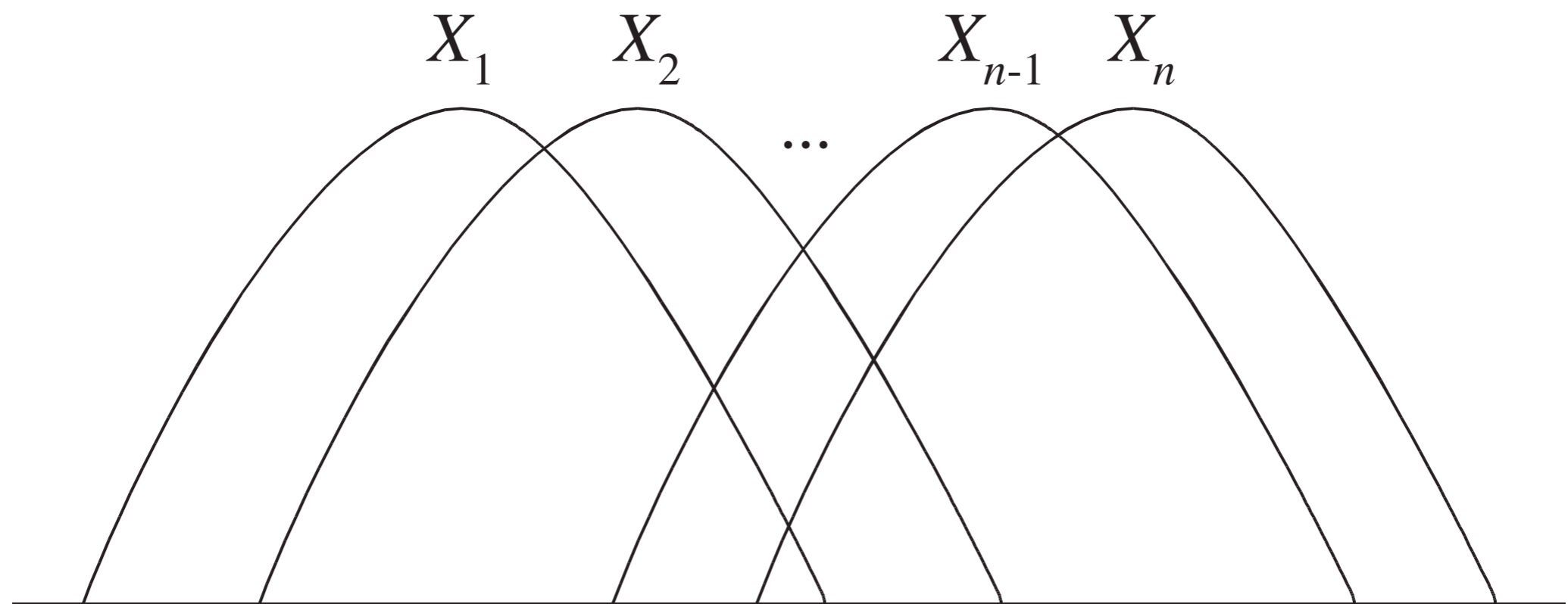
$$\tilde{X}_1^c \cap \tilde{X}_2 \cap \tilde{X}_3^c \cap \tilde{X}_4$$

- The information diagram can be displayed in two dimensions.
- The values of  $\mu^*$  on the remaining atoms correspond to Shannon's information measures and hence are nonnegative. Thus,  $\mu^*$  is a measure.





- For a general  $n$ , the information diagram can be displayed in two dimensions because certain atoms can be suppressed.
- The values of  $\mu^*$  on the remaining atoms correspond to Shannon's information measures and hence are nonnegative. Thus,  $\mu^*$  is a measure.
- See Ch. 12 for a detailed discussion in the context of Markov random field.



## 3.6 Examples of Applications

- To obtain information identities is WYSIWYG.
- To obtain information inequalities:

– If  $\mu^*$  is nonnegative, if  $A \subset B$ , then

$$\mu^*(A) \leq \mu^*(B)$$

because

$$\mu^*(A) \leq \mu^*(A) + \mu^*(B - A) = \mu^*(B)$$

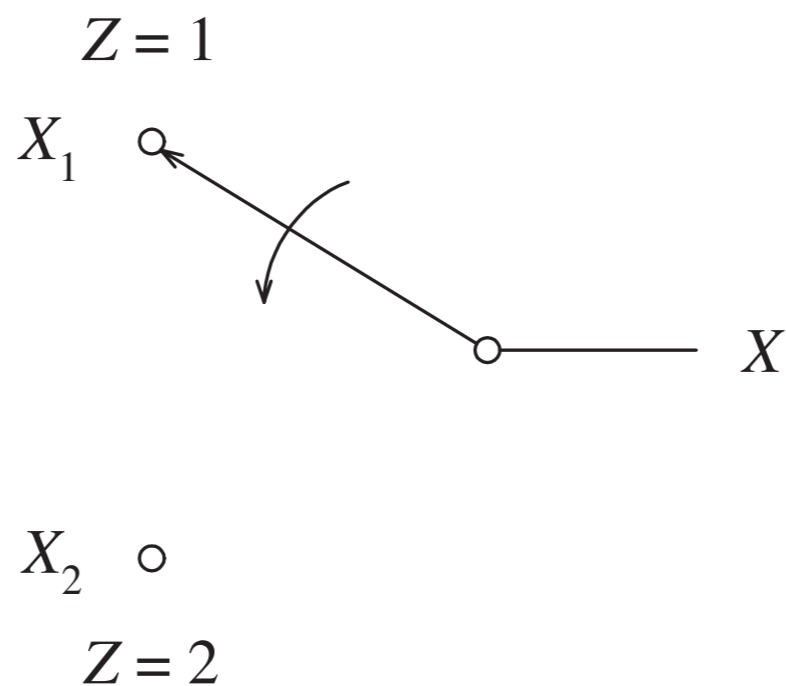
– If  $\mu^*$  is a signed measure, need to invoke the basic inequalities.

**Example 3.12 (Concavity of Entropy)** Let  $X_1 \sim p_1(x)$  and  $X_2 \sim p_2(x)$ .  
Let

$$X \sim p(x) = \lambda p_1(x) + \bar{\lambda} p_2(x),$$

where  $0 \leq \lambda \leq 1$  and  $\bar{\lambda} = 1 - \lambda$ . Show that

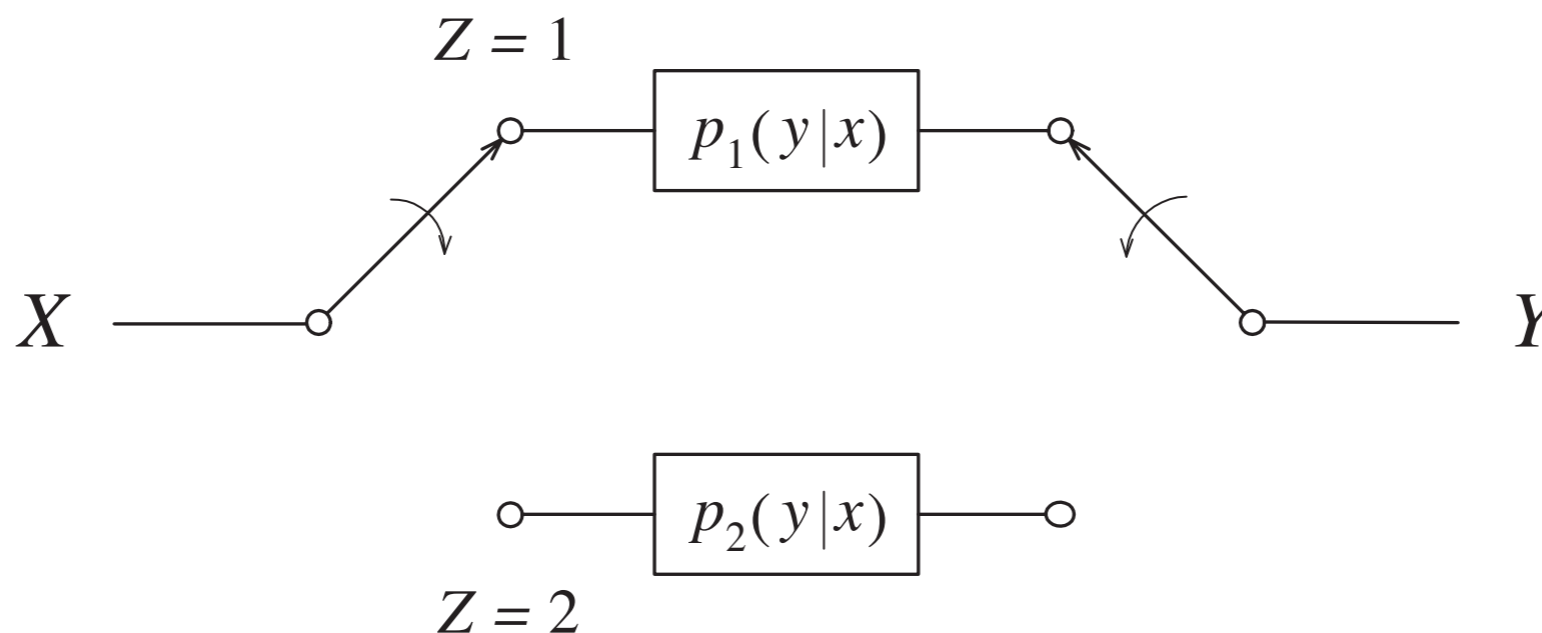
$$H(X) \geq \lambda H(X_1) + \bar{\lambda} H(X_2).$$



**Example 3.13 (Convexity of Mutual Information)** Let

$$(X, Y) \sim p(x, y) = p(x)p(y|x).$$

Show that for fixed  $p(x)$ ,  $I(X; Y)$  is a convex functional of  $p(y|x)$ .

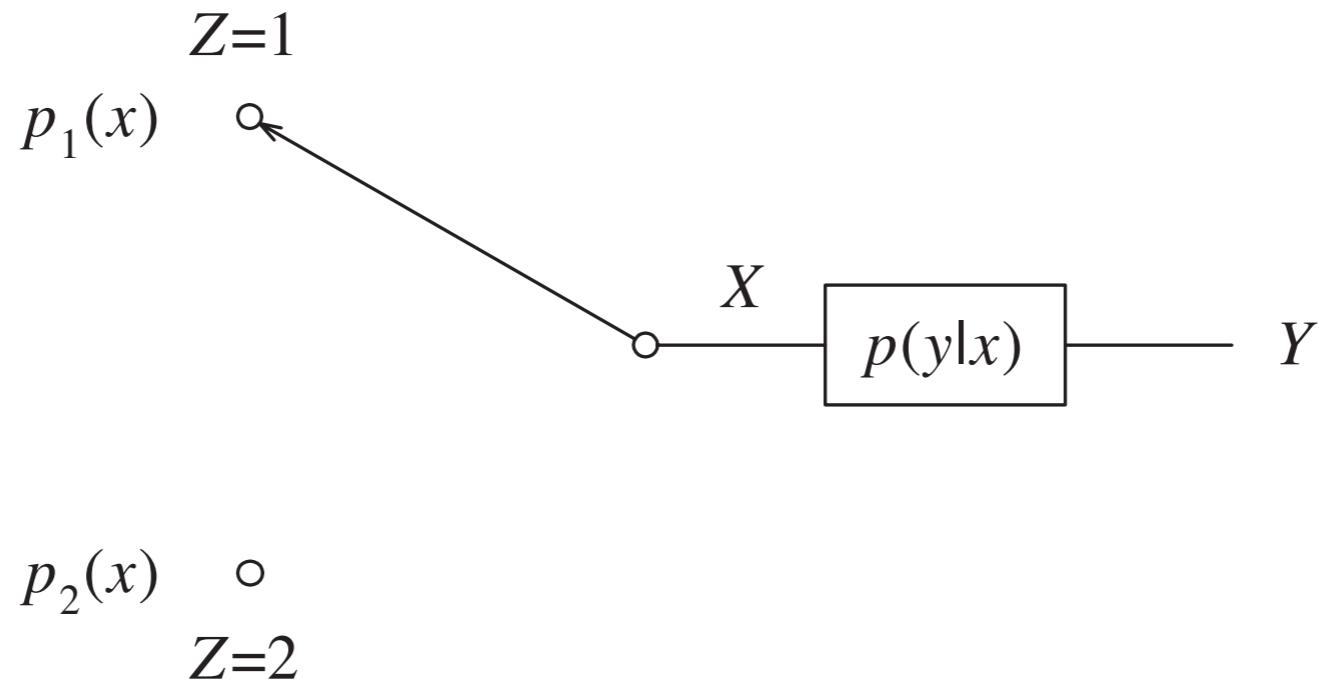


Setup:  $I(X; Z) = 0$ .

**Example 3.14 (Concavity of Mutual Information)** Let

$$(X, Y) \sim p(x, y) = p(x)p(y|x).$$

Show that for fixed  $p(y|x)$ ,  $I(X; Y)$  is a concave functional of  $p(x)$ .



Setup:  $Z \rightarrow X \rightarrow Y$ .

# Shannon's Perfect Secrecy Theorem

- $X$  – plaintext  
 $Y$  – ciphertext  
 $Z$  – key
- Perfect Secrecy:  $I(X; Y) = 0$
- Decipherability:  $H(X|Y, Z) = 0$
- These requirements imply  $H(Z) \geq H(X)$ , i.e., the length of the key is at least the same as the length of the plaintext. Lower bound achievable by “one-time pad”.
- Shannon (1949) gave a combinatorial proof.
- Can readily be proved by an information diagram.

**Example 3.15 (Imperfect Secrecy Theorem)** Let  $X$  be the plain text,  $Y$  be the cipher text, and  $Z$  be the key in a secret key cryptosystem. Since  $X$  can be recovered from  $Y$  and  $Z$ , we have

$$H(X|Y, Z) = 0.$$

Show that this constraint implies

$$I(X; Y) \geq H(X) - H(Z).$$

**Remark** Do not need to make these assumptions about the scheme:

- $H(Y|X, Z) = 0$
- $I(X; Z) = 0$

**Example 3.17 (Data Processing Theorem)** If  $X \rightarrow Y \rightarrow Z \rightarrow T$ , then

- $I(X; T) \leq I(Y; Z)$
- in fact

$$I(Y; Z) = I(X; T) + I(X; Z|T) + I(Y; T|X) + I(Y; Z|X, T)$$



**Example 3.18** If  $X \rightarrow Y \rightarrow Z \rightarrow T \rightarrow U$ , then

$$H(Y) + H(T) = I(Z; X, Y, T, U) + I(X, Y; T, U) + H(Y|Z) + H(T|Z)$$

- Very difficult to discover without an information diagram.
- Instrumental in proving an outer bound for the multiple description problem.

# Highlight of Ch. 12

- The  $I$ -Measure completely characterizes a class of Markov structures called [full conditional independence](#).
- [Markov random field](#) is a special case.
- Markov chain is a special case of Markov random field.
- Analysis of these Markov structures becomes completely set-theoretic.

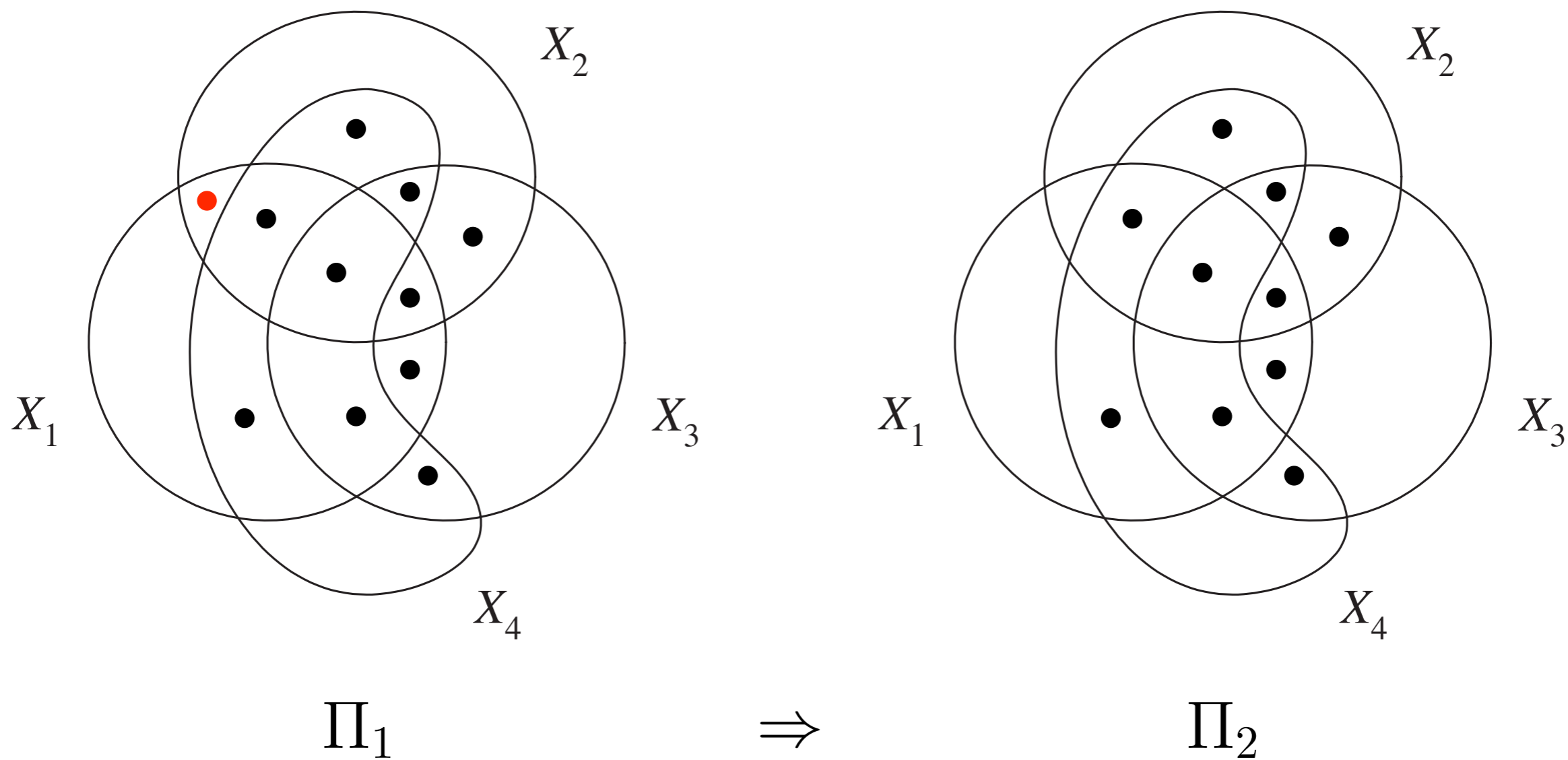
## Example 12.22

$$\Pi_1 : \begin{cases} (X_1, X_2) \perp (X_3, X_4) \\ (X_1, X_3) \perp (X_2, X_4) \end{cases} \Rightarrow \Pi_2 : \begin{cases} (X_1, X_2, X_3) \perp X_4 \\ (X_1, X_2, X_4) \perp X_3 \end{cases}$$

- Each (conditional) independency forces  $\mu^*$  to vanish on the atoms in the corresponding set.
- E.g.,  $(X_1, X_2) \perp (X_3, X_4) \Leftrightarrow \mu^*$  vanishes on the atoms in  $(\tilde{X}_1 \cup \tilde{X}_2) \cap (\tilde{X}_3 \cup \tilde{X}_4)$ .

# Analysis of Example 12.12

$\mu^*$  vanishes on atoms with a dot.



# Proving Information Inequalities

- Information inequalities that are implied by the basic inequalities are called [Shannon-type inequalities](#).
- They can be proved by means of a linear program called [ITIP](#) (Information Theoretic Inequality Prover), developed on Matlab at CUHK (1996):

<http://user-www.ie.cuhk.edu.hk/~ITIP/>

- A version running on C called [Xitip](#) was developed at EPFL (2007):

<http://xitip.epfl.ch/>

- See Ch. 13 and 14 for discussion.

# ITIP Examples

1. `>> ITIP('H(XYZ) <= H(X) + H(Y) + H(Z)')`  
True

2. `>> ITIP('I(X;Z) = 0', 'I(X;Z|Y) = 0', 'I(X;Y) = 0')`  
True

3. `>> ITIP('X/Y/Z/T', 'X/Y/Z', 'Y/Z/T')`  
Not provable by ITIP

4. `>> ITIP('I(Z;U) - I(Z;U|X) - I(Z;U|Y) <= 0.5 I(X;Y) + 0.25 I(X;ZU) + 0.25 I(Y;ZU)')`  
Not provable by ITIP

- #4 is a so-called [non-Shannon-type inequalities](#) which is valid but not implied by the basic inequalities. See Ch. 15 for discussion.