

Readings

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- Key equations; some intuition on theoretical points
- Koller (2009) / Jordan (2003) (need to shorten + hence select + concise)
- BN cannot model a distri. that satisfies $(A \perp C | \{B, D\})$ and $(B \perp D | \{A, C\})$ only.
- UGM \rightarrow undirected edges (prob. interaction)
- similar to BN; parametrisation of MN
 - local interactions
 - global model
- product of local factors, normalised
- normalising constant \rightarrow partition function (MRF in statistical physics)
- MN - connection between factorisation and independence properties

0.43 (Gibbs distn)

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- An undirected graphical model represents a distri $p(X_1, \dots, X_n)$ defined by an undirected graph H , and a set of (positive) potential functions ψ_c associated with cliques of H s.t.
- $$\pi_c(x_c)$$

$$p(x_1, \dots, x_n) = \frac{1}{Z} \prod_{c \in C} \psi_c(x_c) \quad Z = \sum_{x_1, \dots, x_n} \prod_{c \in C} \psi_c(x_c)$$

04.4 (min factor 3.)

- 04.4 (MN factors)
- we say a distri $P(x_1, \dots, x_n)$ with $\psi = \{\psi_1(x_1), \dots, \psi_c(x_c)\}$ factorises over a MN H if each x_c ($c=1, \dots, C$) is a complete subgraph of H
 - Factors that parametrise MN are clique potentials

(*) - informally, subs. with idea of a maximal clique

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- (*) wlog, parametrisation using maximal cliques obscures structure in original set of factors (of a graph)

informally: clique \rightarrow fully connected subset of nodes

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- clique \rightarrow fully connected subset of nodes
- maximal cliques \rightarrow cliques that cannot be extended to include additional nodes without losing property of being fully connected

formally :-

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- For $G = \{E, V\}$, a complete subgraph (clique) is a subgraph $G' = \{V' \subseteq V, E' \subseteq E\}$ such that nodes V' are fully interconnected

- A maximal clique is a complete subgraph s.t. any superset $V'' \supset V'$ is not complete
- A sub-clique is not necessarily a maximal clique

Sub-cliques - can be edges, singletons

Koller (2009): see Box 4.B. - MN for CV

4.3. MN independencies

Similar to Kollerian pres. \rightarrow flows of prob. influence / active trails

04.8

- Let H be an MN structure
- Let $X_1 - \dots - X_k$ be a path in H .
- Let $Z \subseteq X$ be a set of observed variables
- The path $X_1 - \dots - X_k$ is active given Z if none of the X_i s $k=1, \dots, k$ is in Z

allows a definition of separation

04.9 (separation/global independencies)

- We say a set of nodes Z separates X and Y in H , denoted $\text{sep}_H(X; Y | Z)$, if there is no active path between any node $X \in X$ and $Y \in Y$ given Z .
- We define the global independencies associated with H to be:-

$$\mathcal{I}(H) = \{ (X \perp Y | Z) : \text{sep}_H(X; Y | Z) \}$$

Remark:

Independencies $\mathcal{I}(H)$ are precisely those guaranteed to hold for every distri P over H .

sep. criterion sound for detecting indep. properties over H .

(\(\backslash\)) BN \rightarrow connection with independence prop implied by MN structure

+
factorising a distri over the graph

(\(\backslash\)) of both representation

(*)

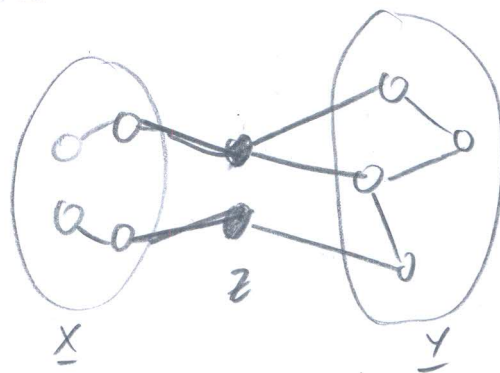
Heuristics for BN, equivalence of:-

Gibbs fact. of

distri P over a graph H

\Leftrightarrow

H is an I-map for P (that is P satisfies Markov ass. $\mathcal{I}(H)$)



4.3.1.1. (soundness)

(11) to 4.3.2. i.e. Gibbs distri satisfies independencies associated with a graph.

i.e. soundness of separation

(factorisation $\xLeftrightarrow[4.2/3.1]{4.1/3.2}$ C.I.)
accord. G

1.4.1.

- let P be a distri over X , and H an MN structure over X

- If P is a Gibbs distri that factorises over H , then H is an I-map for P

other direction i.e. C.I. of distri \rightarrow factorisation: Hammersley-Clifford Theorem

- unlike for BN, HCT does not hold in general.

- require additional assumption that P is a positive distri

1.4.2

- let P be a positive distri over X , and H a Markov network graph over X .

- If H is an I-map for P , then P is a Gibbs distri that factorises over H .

(*) for positive distris, the global independencies imply that distri factorises according to the network structure.

(*) for this class of distributions, we have that a distribution P factorises over a Markov network if and only if H is an I-map of P .

~~(*)~~ lecture def An I-M H is an I-map for a distri P if $I(H) \subseteq I(P)$ i.e. P entails $I(H)$

(*) If P is a Gibbs distri over H , then H is an I-map of P .

• soundness of separation as criterion for detecting independencies in MN.

- any distri that factorises over G satisfies the independence ass. implied by separation

- completeness - strong version of completeness does not hold

- It is NOT the case that every pair of nodes X and Y that are not separated in H are dependent in every distribution P which factorises over H
(use Markov)

1.4.3

- let H be a MN structure.

- If X and Y are not separated given Z in H , then X and Y are dependent given Z in some distri P that factorises over H .

- same arguments as 1.3.5 to conclude:-

② for almost all distri P that factorise over H (all distri. except for a set of measure 0 in space of factor param.), we have $I(P) = I(H)$.

- our defn of $I(H)$ is maximal one.

- for any independence assertion that is not a consequence of separation in H , we can always find a counterexample distri P that factorises over H .

4.3.2. indep. revisited

BN: local indep. (each node is indep. of nondecs. given parents)

Global indep. (induced by d-sep)

- showed that these are equiv, in the sense of one implies the other.

Q: (1) to BN; can we provide local indep. induced by MN, analogously to local indep. of BN

②: 3 diff poss. defn. of independencies associated with network structure
two local, one global in def 4.9.

4.3.2.1. - Local Markov ass.

D.4.10 → intuitively, two variables directly connected; potential for direct correlation in an unmediated way.

- conversely, two vars not directly linked, some way of redrawing c.i.
- X and Y indep given all other nodes.

D.4.10 (Pairwise independencies)

Let H be a MN

We define pairwise independencies associated with H to be:-

$$I_p(H) = \{ (X \perp Y \mid X - \{X, Y\} : \{X, Y\} \notin \mathcal{M}_H) \}$$

D.4.11 → analogue to local indep. associated with B.N.

4.11. (Markov blanket)

For a given graph H , we define the Markov blanket of X in H , $MB_H(X)$ to be the neighbors of X in H .

We define the local independencies associated with H to be:-

$$I_l(H) = \{ (X \perp X - \{X\} - MB_H(X) \mid MB_H(X) : X \in \mathcal{X}) \}$$

i.e. local independencies state that X is indep. of nodes in graph given immed. neighbours.

- we will show that these local indep. ass. hold for any distri that factorizes over H , so that X 's Markov blanket in H truly does sep. it from all other variables.

4.3.2.2. - relationships between Markov properties

- 3 sets of indep. assertions assoc. with network structure H .
- For general distri $I_p(H)$ is weaker than $I_c(H)$ is weaker than $I(H)$.
- ~~All 3 are eq.~~ (*) All 3 are equivalent for positive distri

Prop 4.3

- For any MN H , and any distri P , we have that if $P \models I_c(H)$ then $P \models I_p(H)$

Prop 4.4

- For any MN H , and any distri P , we have that if $P \models I(H)$ then $P \models I_c(H)$

Th 4.4

- Let P be a positive distri. If P satisfies $I_p(H)$, then P satisfies $I(H)$.

Corollary 4.1

- The following statements are equivalent for a positive distri P .

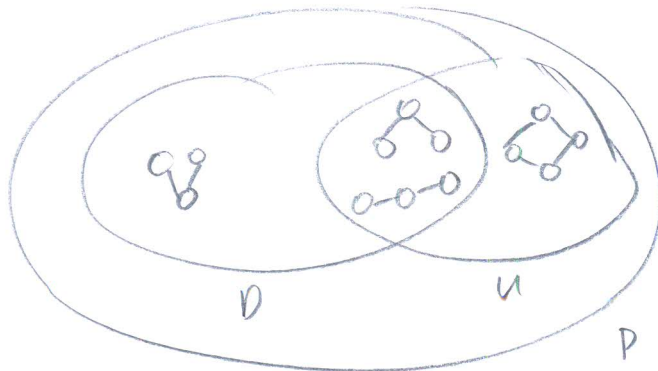
1. $P \models I_c(H)$
2. $P \models I_p(H)$
3. $P \models I(H)$

Def 4.1

- An MN H is a perfect-map for P if for any $\underline{X}, \underline{Y}, \underline{Z}$, we have that

$$\text{sep}_H(\underline{X} : \underline{Y} | \underline{Z}) \Leftrightarrow P \models (\underline{X} \perp \underline{Y} | \underline{Z})$$

Theorem: not every distri has a perfect map as UGM



from here on, Jordan (2003)

- exponential form

- constraining clique potentials to be tree invariant and possibly

Q(1): what effect does this have on equivalence of local and global Markov properties?

represent a clique potential as: ^(*) $\phi_c(x_c) = \exp\{-\phi_c(x_c)\}$

$\phi_c(x_c)$ - a 'potential'

Additive structure: $p(x) = \frac{1}{Z} \prod_{c \in C} \exp\{-\phi_c(x_c)\}$

$$= \frac{1}{Z} \exp\left\{-\sum_{c \in C} \phi_c(x_c)\right\} = \frac{1}{Z} \exp\{-H(x)\}$$

$$H(x) = \sum_{c \in C} \phi_c(x_c)$$

$H(x)$ - free energy

'Boltzmann distri'

some notable forms / graph topologies:-

Boltzmann machines

fully connected graph, pairwise edge pot., binary valued nodes $\{-1, 1\}$

$$p(x_1, x_2, x_3, x_4) = \frac{1}{Z} \exp\left\{\sum_{i,j} \phi_{ij}(x_i, x_j)\right\} = \frac{1}{Z} \exp\left\{\sum_{i,j} \theta_{ij} x_i x_j + \sum_i \alpha_i x_i + C\right\}$$

call negy fn:-

$$E(x) = \sum_{i,j} (x_i - \mu) \theta_{ij} (x_j - \mu) = (x - \mu)^T \Theta (x - \mu)$$

new technique to learn this model, recover graph str. from data.

g models

model energy of a physical system (atom interaction)

regular grid topology

Multi-state \rightarrow Potts.

$$p(x) = \frac{1}{Z} \exp\left\{\sum_{i,j \in N_i} \theta_{ij} x_i x_j + \sum_i \theta_{i0} x_i\right\}$$

Restricted Boltzmann Machines

$$p(x, y | \theta) = \exp \left\{ \sum_i \theta_i \phi_i(x_i) + \sum_j \theta_j \phi_j(y_j) + \sum_{i,j} \theta_{i,j} \phi_{i,j}(x_i, y_j) - A(\theta) \right\}$$

- see paper

CRFs

- undirected graph rep. ; encode cond. distri $p(y|x)$ y_i - target x - obs.

$$p_\theta(y|x) = \frac{1}{Z(\theta, x)} \exp \left\{ \sum_i \theta_i \phi_i(x, y_i) \right\}$$