

CS262a Bayesian Networks

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Preface

I shall organize everything based on the chapters later.

0.1 Principle Logical Forms

Inconsistent. Something that never holds; $\text{Mods}(\cdot) = \emptyset$; $\Pr(\alpha) = 0$

Valid. Something that always holds; $\text{Mods}(\cdot) = \Omega$; $\Pr(\alpha) = 1$

Equivalent. $\text{Mods}(\alpha) = \text{Mods}(\beta)$

Mutual Exclusive. $\text{Mods}(\alpha) \cap \text{Mods}(\beta) = \emptyset$

Exhaustive. $\text{Mods}(\alpha) \cup \text{Mods}(\beta) = \Omega$

Entailment / Implication. $\alpha \models \beta \triangleq \text{Mods}(\alpha) \subseteq \text{Mods}(\beta)$

0.2 Equivalent Forms

- $\text{Mods}(\alpha \wedge \beta) = \text{Mods}(\alpha) \cap \text{Mods}(\beta)$
- $\text{Mods}(\alpha \vee \beta) = \text{Mods}(\alpha) \cup \text{Mods}(\beta)$
- $\text{Mods}(\neg\alpha) = \overline{\text{Mods}(\alpha)}$

0.3 Instantiation Agreement

Two instantiation, each of which can cover a subset of different variables, are said to be compatible with each other if they agree on all common variables. Denoted as $\mathbf{x} \sim \mathbf{y}$.

0.4 Information Theory

Entropy.

$$\text{ENT}(X) = - \sum_x \text{Pr}(x) \log \text{Pr}(x) \quad (0.1)$$

where $0 \log 0 = 0$ by convention. With a higher entropy, we say that it is more chaotic.

Conditional Entropy.

$$\text{ENT}(X|Y) = \sum_y \text{Pr}(y) \text{ENT}(X|y) \quad \text{where} \quad \text{ENT}(X|y) = - \sum_x \text{Pr}(x|y) \log \text{Pr}(x|y) \quad (0.2)$$

Conditioning never increases the entropy, i.e.

$$\text{ENT}(X|Y) \leq \text{ENT}(X) \quad (0.3)$$

Mutual Information

$$\text{MI}(X; Y) = \sum_{x,y} \text{Pr}(x, y) \log \frac{\text{Pr}(x, y)}{\text{Pr}(x) \text{Pr}(y)} \quad (0.4)$$

$$= \text{ENT}(X) - \text{ENT}(X|Y) \quad (0.5)$$

$$= \text{ENT}(Y) - \text{ENT}(Y|X) \quad (0.6)$$

Conditional Mutual Information

$$\text{MI}(X; Y|Z) = \sum_{x,y,z} \text{Pr}(x, y, z) \log \frac{\text{Pr}(x, y|z)}{\text{Pr}(x|z) \text{Pr}(y|z)} \quad (0.7)$$

$$= \text{ENT}(X|Z) - \text{ENT}(X|Y, Z) \quad (0.8)$$

$$= \text{ENT}(Y|Z) - \text{ENT}(Y|X, Z) \quad (0.9)$$

0.5 Bayesian Conditioning

Bayesian Condition is specified by the formula

$$\text{Pr}(\alpha|\beta) = \frac{\text{Pr}(\alpha \wedge \beta)}{\text{Pr}(\beta)} \quad (0.10)$$

In particular, not to be confused with Bayesian inference (to be added later).

0.6 Independence and Notations

Independence.

$$\alpha \perp\!\!\!\perp \beta \iff \Pr(\alpha|\beta) = \Pr(\alpha) \vee \Pr(\beta) = 0 \quad (0.11)$$

$$\iff \Pr(\alpha \wedge \beta) = \Pr(\alpha)\Pr(\beta) \quad (0.12)$$

Conditional Independence.

$$(\alpha \perp\!\!\!\perp \beta)|\gamma \iff \Pr(\alpha|\beta \wedge \gamma) = \Pr(\alpha|\gamma) \vee \Pr(\beta \wedge \gamma) = 0 \quad (0.13)$$

$$\iff \Pr(\alpha \wedge \beta|\gamma) = \Pr(\alpha|\gamma)\Pr(\beta|\gamma) \vee \Pr(\gamma) = 1 \quad (0.14)$$

Set Independence

$$I_{\Pr}(X, Z, Y) \iff (x \perp\!\!\!\perp y)|z, \quad \forall x, y, z \in X, Y, Z \quad (0.15)$$