

Machine Learning I

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Machine Learning for Computer Vision
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<https://mlcv.cs.tu-dresden.de/courses/25-winter/ml1/>

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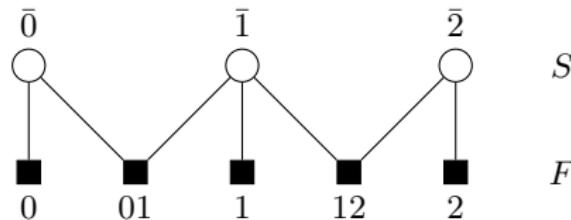
Conditional Graphical Models

Contents. This part of the course is about supervised structured learning of conditional graphical models.

Definition. For any factor graph $G = (S, F, E)$, a function $H : \{0, 1\}^S \rightarrow \mathbb{R}$ is said to **factorize** w.r.t. G iff, for every $f \in F$, there exists a function $h_f : \{0, 1\}^{S_f} \rightarrow \mathbb{R}$, called a **factor** of H , such that

$$\forall y \in \{0, 1\}^S: \quad H(y) = \sum_{f \in F} h_f(y_{S_f}) . \quad (1)$$

Example: A function $H : \{0, 1\}^S \rightarrow \mathbb{R}$ factorizes w.r.t. the factor graph



iff there exist suitable functions $h_0, h_{01}, h_1, h_{12}, h_2$ such that, for any $y \in \{0, 1\}^S$: $H(y) = h_0(y_{\bar{0}}) + h_1(y_{\bar{1}}) + h_2(y_{\bar{2}}) + h_{01}(y_{\bar{0}}, y_{\bar{1}}) + h_{12}(y_{\bar{1}}, y_{\bar{2}})$.

Definition. A tuple $(S, F, E, \{X_f\}_{f \in F}, \Theta, \{h_f\}_{f \in F})$ is called a **conditional graphical model** with attribute space $X := \prod_{f \in F} X_f$ and parameter space Θ iff the following conditions hold:

- ▶ (S, F, E) is a factor graph
- ▶ $\Theta \neq \emptyset$
- ▶ For every $f \in F$:
 - ▶ X_f is non-empty, called the **attribute space** of f
 - ▶ $h_f : \Theta \rightarrow \mathbb{R}^{X_f \times \{0,1\}^{S_f}}$, called a **factor**.

The family $H : \Theta \rightarrow \mathbb{R}^{X \times \{0,1\}^S}$ such that

$$\forall \theta \in \Theta \ \forall x \in X \ \forall y \in \{0,1\}^S : \quad H_\theta(x, y) = \sum_{f \in F} h_{f\theta}(x_f, y_{S_f}) \quad (2)$$

is called the family of **energy functions** of the conditional graphical model.

Family of Functions

- We consider a conditional graphical model $(S, F, E, \{X_f\}_{f \in F}, \Theta, \{h_f\}_{f \in F})$ and its family H of energy functions.
- We assume that Θ is a finite-dimensional, real vector space, i.e., there exists a finite, non-empty set J and $\Theta = \mathbb{R}^J$.
- We assume that every function h_f is linear in Θ , i.e., for every $f \in F$, there exists a $\varphi_f : X_f \times \{0, 1\}^{S_f} \rightarrow \mathbb{R}^J$ such that for any $x_f \in X_f$, any $y_{S_f} \in \{0, 1\}^{S_f}$ and any $\theta \in \Theta$:

$$h_{f\theta}(x_f, y_{S_f}) = \langle \theta, \varphi_f(x_f, y_{S_f}) \rangle \quad (3)$$

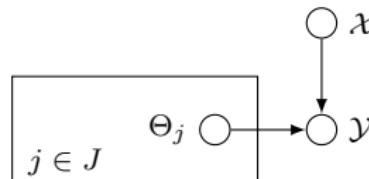
Conditional Graphical Models

For convenience, we define $\xi : X \times \{0, 1\}^S \rightarrow \mathbb{R}^J$ such that for any $x \in X$ and any $y \in \{0, 1\}^S$:

$$\xi(x, y) = \sum_{f \in F} \varphi_f(x_f, y_{S_f}) \quad (4)$$

Thus, we obtain for any $\theta \in \Theta$, any $x \in X$ and any $y \in Y$:

$$\begin{aligned} H_\theta(x, y) &= \sum_{f \in F} h_{f\theta}(x_f, y_{S_f}) \\ &= \sum_{f \in F} \langle \theta, \varphi_f(x_f, y_{S_f}) \rangle \\ &= \left\langle \theta, \sum_{f \in F} \varphi_f(x_f, y_{S_f}) \right\rangle \\ &= \langle \theta, \xi(x, y) \rangle \quad (5) \end{aligned}$$



Probabilistic Model

- ▶ Let \mathcal{X} be a random variable whose value is an element $x \in X$ of the attribute space.
- ▶ Let \mathcal{Y} be a random variable whose value is a combination of decisions $y \in \{0, 1\}^S$
- ▶ For any $j \in J$, let Θ_j a random variable whose value is a parameter $\theta_j \in \mathbb{R}$

Conditional Graphical Models

Factorization

- We assume:

$$P(\mathcal{X}, \mathcal{Y}, \Theta) = P(\mathcal{Y} \mid \mathcal{X}, \Theta) P(\mathcal{X}) \prod_{j \in J} P(\Theta_j) \quad (6)$$

- Thus:

$$\begin{aligned} P(\Theta \mid \mathcal{X}, \mathcal{Y}) &= \frac{P(\mathcal{X}, \mathcal{Y}, \Theta)}{P(\mathcal{X}, \mathcal{Y})} \\ &= \frac{P(\mathcal{Y} \mid \mathcal{X}, \Theta) P(\mathcal{X}) \prod_{j \in J} P(\Theta_j)}{P(\mathcal{X}, \mathcal{Y})} \\ &\propto P(\mathcal{Y} \mid \mathcal{X}, \Theta) \prod_{j \in J} P(\Theta_j) \end{aligned} \quad (7)$$

Conditional Graphical Models

Distributions

Definition. For any conditional graphical model, the **partition function** $Z: X \times \Theta \rightarrow \mathbb{R}$ and **Gibbs distribution** $p: X \times \{0, 1\}^S \times \Theta \rightarrow [0, 1]$ are defined by the forms

$$Z(x, \theta) = \sum_{y \in \{0, 1\}^S} e^{-H_\theta(x, y)} \quad (8)$$

$$p(y, x, \theta) = \frac{1}{Z(x, \theta)} e^{-H_\theta(x, y)} \quad (9)$$

We consider a $\sigma \in \mathbb{R}^+$ and

$$p_{\mathcal{Y}|\mathcal{X}, \Theta}(y, x, \theta) = \frac{1}{Z(x, \theta)} e^{-H_\theta(x, y)} \quad (10)$$

$$\forall j \in J: \quad p_{\Theta_j}(\theta_j) = \frac{1}{\sigma \sqrt{2\pi}} e^{-\theta_j^2/2\sigma^2}. \quad (11)$$

Conditional Graphical Models

Lemma. Estimating maximally probable parameters θ , given attributes x and decisions y , i.e.,

$$\operatorname{argmax}_{\theta \in \mathbb{R}^J} p_{\Theta|x,y}(\theta, x, y)$$

is identical to the supervised structured learning problem w.r.t. L , R and λ such that

$$L(H_\theta(x, \cdot), y) = H_\theta(x, y) + \ln Z(x, \theta) \quad (12)$$

$$= H_\theta(x, y) + \ln \sum_{y' \in \{0,1\}^S} e^{-H_\theta(x, y')} \quad (13)$$

$$= \langle \theta, \xi(x, y) \rangle + \ln \sum_{y' \in \{0,1\}^S} e^{-\langle \theta, \xi(x, y') \rangle} \quad (14)$$

$$R(\theta) = \|\theta\|_2^2 \quad (15)$$

$$\lambda = \frac{1}{2\sigma^2} \quad (16)$$

Conditional Graphical Models

Lemma: The first and second partial derivatives of the logarithm of the partition function have the forms

$$\frac{\partial}{\partial \theta_j} \ln Z = \frac{1}{Z(x, \theta)} \sum_{y' \in \{0,1\}^S} (-\xi_j(x, y')) e^{-\langle \theta, \xi(x, y') \rangle} \quad (17)$$

$$= \mathbb{E}_{y' \sim p_{\mathcal{Y}|\mathcal{X}, \Theta}} (-\xi_j(x, y')) \quad (18)$$

$$\begin{aligned} \frac{\partial^2}{\partial \theta_j \partial \theta_k} \ln Z &= \mathbb{E}_{y' \sim p_{\mathcal{Y}|\mathcal{X}, \Theta}} (\xi_j(x, y') \xi_k(x, y')) \\ &\quad - \mathbb{E}_{y' \sim p_{\mathcal{Y}|\mathcal{X}, \Theta}} (\xi_j(x, y')) \mathbb{E}_{y' \sim p_{\mathcal{Y}|\mathcal{X}, \Theta}} (\xi_k(x, y')) \\ &= \text{COV}_{y' \sim p_{\mathcal{Y}|\mathcal{X}, \Theta}} (\xi_j(x, y'), \xi_k(x, y')) \end{aligned} \quad (19)$$

Lemma: Supervised structured learning of a conditional graphical model is a convex optimization problem.

Lemma: Estimating maximally probable decisions y , given attributes x and parameters θ , i.e.

$$\operatorname{argmax}_{y \in \{0,1\}^S} p_{Y|X,\Theta}(x, y, \theta) \quad (20)$$

is identical to the structured inference problem with $\hat{H}(x, y) = H_\theta(x, y)$.

Conditional Graphical Models

Summary. Supervised structured learning of conditional graphical models whose factors are linear functions is a convex optimization problem.