

A Toy Example for EM Algorithm

Setup:



$$x \in \{0, 1\}$$

$$P_x(0) \triangleq \theta_0, \quad P_x(1) \triangleq \theta_1$$

$$y \in \{0, 1\}$$

$$P_{Y|x}(i|j) \triangleq \theta_{ij}, \quad \begin{matrix} i \in \{0, 1\} \\ j \in \{0, 1\} \end{matrix}$$

1. Single observation

$$\boxed{y = 1}$$

x hidden.

Goal: find $\theta = (\theta_0, \theta_1, \theta_{0|0}, \theta_{0|1}, \theta_{1|0}, \theta_{1|1})$ s.t. $P_Y(y; \theta)$ is maximized.

Solution: EM algo.

Initialization: $\theta_0^{(0)} = \theta_1^{(0)} = 1/2$, $\theta_{0|0}^{(0)} = 0.9 = \theta_{1|1}^{(0)}$, $\theta_{1|0}^{(0)} = 0.1 = \theta_{0|1}^{(0)}$

These numbers are just made up for the toy example, can be anything.

E-step: $q^{(1)}(x) = P_{x|Y}(x|y)$

$$\therefore q^{(1)}(0) = P_{x|Y}(0|1) = \frac{P_{x,Y}(0,1)}{P_Y(1)} = \frac{P_x(0) P_{Y|x}(1|0)}{P_x(0) P_{Y|x}(1|0) + P_x(1) P_{Y|x}(1|1)}$$

$$\text{using } \theta^{(0)} \quad \frac{0.1 \times \frac{1}{2}}{0.1 \times \frac{1}{2} + 0.9 \times \frac{1}{2}} = 0.1$$

similarly $q^{(1)}(1) = 0.9$

M-step: $\theta^{(1)} = \underset{\theta}{\operatorname{argmax}} \underbrace{E_{q^{(1)}} [\log P_{x,Y}(x, y; \theta)]}_{(*)}$

$$(*) = \sum_{x=0}^1 q^{(1)}(x) \log P_{x,Y}(x, 1; \theta)$$

$$= q^{(1)}(0) [\log \theta_0 + \log \theta_{0|0}] + q^{(1)}(1) [\log \theta_1 + \log \theta_{1|1}] \quad (**)$$

want to maximize (**) subject to:

$$\theta_0 + \theta_1 = 1, \quad \theta_0, \theta_1, \theta_{0|0}, \theta_{1|1} \in [0, 1]$$

$$\Rightarrow \theta_0^{(1)} = 0.1 \quad \theta_1^{(1)} = 0.9 \quad \theta_{0|0}^{(1)} = 1 \quad \theta_{1|0}^{(1)} = 0$$

$$\theta_{0|1}^{(1)} = 0 \quad \theta_{1|1}^{(1)} = 1$$

use Lagrangian multipliers. ~~the derivative~~ ≥ 0

2. Multiple (IID) Observations

$$y^{(1)} = 1, y^{(2)} = 0$$

$x^{(1)} x^{(2)}$ hidden.

$$\log P_Y(y^{(1)}, y^{(2)}; \theta) = \log \sum_{x^{(1)}} \sum_{x^{(2)}} P_{X,Y}(x^{(1)}, x^{(2)}, y^{(1)}, y^{(2)}; \theta)$$

$$\geq \mathbb{E}_{q(x^{(1)}, x^{(2)} | y^{(1)}, y^{(2)})} [\log P_{X,Y}(x^{(1)}, x^{(2)}, y^{(1)}, y^{(2)}; \theta)]$$

E-step

$$q(x^{(1)}, x^{(2)} | y^{(1)}, y^{(2)}) = P(x^{(1)}, x^{(2)} | y^{(1)}, y^{(2)})$$

$$= P(x^{(1)} | y^{(1)}) \cdot P(x^{(2)} | y^{(2)})$$

due to independence btw $(x^{(1)}, y^{(1)})$ & $(x^{(2)}, y^{(2)})$

$$\Rightarrow q^{(1)}(0, 0 | 1, 0) = \cancel{0.1 \times 0.9} = 0.1 \times 0.9 = 0.09$$

$$q^{(1)}(0, 1 | 1, 0) = 0.1 \times 0.1 = 0.01$$

$$q^{(1)}(1, 0 | 1, 0) = 0.9 \times 0.9 = 0.81$$

$$q^{(1)}(1, 1 | 1, 0) = 0.9 \times 0.1 = 0.09$$

(Computation of $P(x^{(i)} | y^{(i)})$: see 1^o)

M-step: $\mathbb{E}_{q(\cdot, \cdot | y^{(1)}, y^{(2)})} [\log P_{X,Y}(x^{(1)}, x^{(2)}, y^{(1)}, y^{(2)}; \theta)]$

$$= \sum_{x^{(1)}=0}^1 \sum_{x^{(2)}=0}^1 q^{(1)}(x^{(1)}, x^{(2)}) \cdot \log P_{X,Y}(x^{(1)}, x^{(2)}, 1, 0; \theta)$$

$$= 0.09 (\log \theta_0 + \log \theta_0 + \log \theta_{10} + \log \theta_{010}) \leftarrow x^{(1)}=0, x^{(2)}=0$$

$$+ 0.01 (\log \theta_0 + \log \theta_1 + \log \theta_{10} + \log \theta_{011}) \quad 0, 1$$

$$+ 0.81 (\log \theta_1 + \log \theta_0 + \log \theta_{11} + \log \theta_{010}) \quad 1, 0$$

$$+ 0.09 (\log \theta_1 + \log \theta_1 + \log \theta_{11} + \log \theta_{011}) \quad 1, 1$$

$$= \log \theta_0 + \log \theta_1 + 0.9 \log \theta_{010} + 0.1 \log \theta_{10} + 0.1 \log \theta_{011} + 0.9 \log \theta_{11}$$

subject to $\theta_0 + \theta_1 = 1$ $\theta_{010} + \theta_{110} = 1$ $\theta_{011} + \theta_{111} = 1$

Use Lagrangian multiplier $\Rightarrow \theta_0^{(1)} = \frac{1}{2} = \theta_1^{(1)}$

$$\theta_{010}^{(1)} = 0.9 = \theta_{111}^{(1)} \quad \theta_{110}^{(1)} = 0.1 = \theta_{011}^{(1)}$$

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