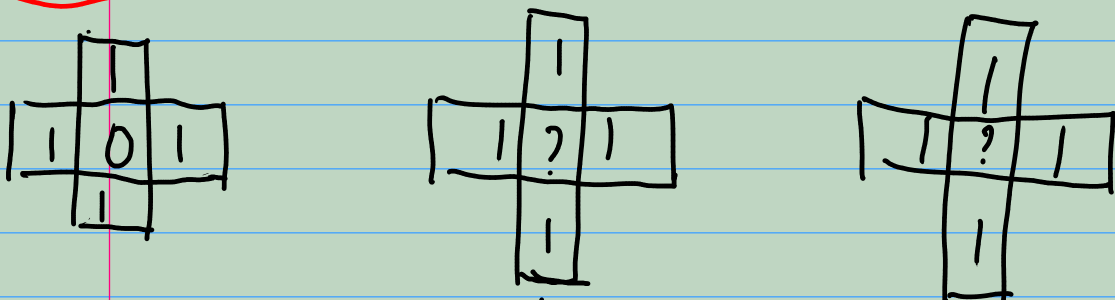
Why estimate β_z is incorrect, given α.



G sub1 sub2

when generating data g_s depends on g_r

at sampling, g_s depends on g_r and z_s

so it is hard to get value "0"

$z \longrightarrow X$ Why does not happen on standard Hidden Markov model?

Because x_r is independent of its neighbors

$$p(z_s | x_s) \propto p(z_s | z_r) \cdot p(x_s | z_s)$$

Graphcuts Optimization

Convert Sampling Problem to Graphcuts.

$$p(G) = \frac{1}{C} \exp\left\{ -\beta \sum_{(r,s)} [g_r \neq g_s] \right\}$$

$$p(z|G) = \frac{1}{C} \exp\left\{ -\alpha \sum_{s} [z_s \neq g_s] - \beta_z \sum_{(r,s)} [z_r \neq z_s] \right\}$$

$$u(G) = \beta \sum_{(r,s)} [g_r \neq g_s]$$

$$u(z|G) = \alpha \sum_{s} [z_s \neq g_s] + \beta_z \sum_{(r,s)} [z_r \neq z_s]$$

$$p(X|z) = \frac{1}{\sqrt{2\pi}\,\sigma} \exp\left\{ -\frac{(X-\mu)^2}{2\sigma^2} \right\}$$

$$u(X|z) = \log\sigma + \frac{(x-\mu)^2}{2\sigma^2}$$

$$obj = \log p(G, z, X)$$

$$\arg\max \log p(G, z, X) = \arg\min -\log p(G, z, X)$$

$$= u(G, z, X)$$

$$\log p(G, z, X) = \log p(G) + \log p(z|G) + \log p(X|z)$$

$$-\log p(G, z, X) = -\log p(G) - \log p(z|G) - \log p(X|z)$$

$$u(G, z, X) = u(G) + u(z|G) + u(X|z)$$

Given G.

$$\hat{z} = \arg\min_{z} U(G, z, X)$$

$$= \arg\min \; U(z|G) + U(X|z)$$

$$Q(z) = U(z|G) + U(X|z)$$ Obj function

$$= \alpha \sum_{s} [z_s \neq g_s] + \beta_z \sum_{(r,s)} [z_s \neq z_r]$$

$$+ \log\sigma + \sum_{s} \left(\log\sigma + \frac{(x-\mu)^2}{2\sigma^2} \right)$$

(μ and σ is fun of z)

= label cost + smooth cost + data cost