

**Minimal energy maximal
entropy**

A Mean field approach

Minimize

$$E(\delta) = \frac{1}{2} \sum_m \sum_n \delta_m^T C(m, n) \delta_n$$

Subject to $\sum_i \delta_{mi} = 1, \delta_{mi} \in \{0, 1\}$

$$\frac{\partial E}{\partial \delta_{mi}}$$

Minimize

$$E(\delta) = \frac{1}{2} \sum_m \sum_n \delta_m^T C(m, n) \delta_n$$

Subject to $\sum_i \delta_{mi} = 1, \delta_{mi} \in \{0, 1\}$

Probabilistic approach: expectation maximization

- Let $p_{ij} \propto \exp(u_{ij})$

- $\sum_j p_{ij} = 1$

An auxiliary variable

- Minimal energy $E(\delta)$ and maximal entropy

$$-\sum_i \sum_j p_{ij} \log p_{ij}$$

p_{ij} represents the probability of the j th bit δ_{ij} being active, $p_{ij} \in [0,1]$

$$\delta_i = [\delta_{i1}, \dots, \delta_{ij}, \dots, \delta_{in}], \delta_{ij} \in \{0,1\}$$

δ_i is a unitary vector of binary elements

$$\sum_j \delta_{ij} = 1$$

Unitary
condition

A probabilistic model assumes δ_i as a random variable.

$$\delta_i \in \{e_1, \dots, e_n\}$$

e_i is a unitary vector of n binary elements with the i th element one

$$p_{ij} = \Pr(\delta_i = e_j) \propto \exp(u_{ij})$$

Find the expectation of δ

Find the entropy of δ

$$e_1 = [1, 0, \dots, 0]^T$$

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$$e_i = [0, 0, \dots, 0, 1, 0, \dots, 0]^T$$

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$$e_n = [0, 0, \dots, 0, 1]^T$$

Let $p_{ij} = K \exp(u_{ij})$

Since $\sum_j p_{ij} = 1,$

$$\sum_j p_{ij} = \sum_j K \exp(u_{ij}) = 1$$

Softmax
Operation

$$K = \frac{1}{\sum_j \exp(u_{ij})}, \quad p_{ij} = \frac{\exp(u_{ij})}{\sum_h \exp(u_{ih})}$$

p_{ij} represents the probability of the j th bit δ_{ij} being active, $p_{ij} \in [0,1]$

Expectation of δ_i

$$= [p_{i1}, \dots, p_{ij}, \dots, p_{in}]^T$$

$$= \left[\frac{\exp(u_{i1})}{\sum_h \exp(u_{ih})}, \dots, \frac{\exp(u_{ij})}{\sum_h \exp(u_{ih})}, \dots, \frac{\exp(u_{in})}{\sum_h \exp(u_{ih})} \right]^T$$

Entropy of δ

$$p_{ij} = \frac{\exp(u_{ij})}{\sum_h \exp(u_{ih})},$$

$$= - \sum_i \sum_j p_{ij} \log p_{ij}$$

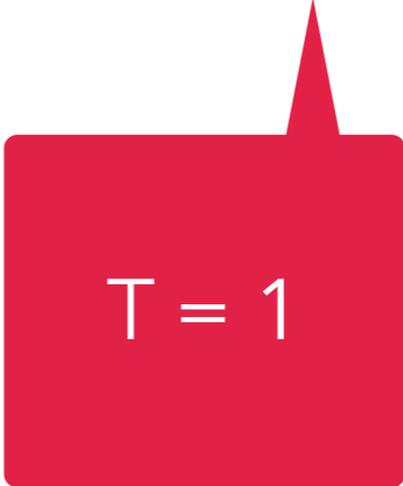
$$= - \sum_{ij} (p_{ij} u_{ij} - p_{ij} \log \sum_h \exp(u_{ih})) = - \sum_{ij} p_{ij} u_{ij} + \log \sum_h \exp(u_{ih})$$

$$p_{ij} = \frac{\exp(u_{ij})}{\sum_h \exp(u_{ih})},$$

Mean Field Approximation: Minimal **mean** energy and maximal entropy

Directly substituting
mean to energy

Free energy
= mean energy - entropy



$T = 1$

Mean Energy is approximated by the energy of mean,

$$E(\langle \delta \rangle) = \sum_{ij} p_i^T C_{ij} p_j \quad \text{approximates} \quad \langle E(\delta) \rangle$$

$$p_i = \langle \delta_i \rangle$$

intractable in computation $\langle E(\delta) \rangle = \sum_{\delta} E(\delta) Pr(\delta)$

Free energy

$$= \sum_{ij} p_i^T C_{ij} p_j - \left(- \sum_i \sum_j p_{ij} \log p_{ij} \right)$$

$$= \sum_i \sum_j p_i^T C_{ij} p_j + \sum_{ij} (p_{ij} u_{ij} - p_{ij} \log \sum_h \exp(u_{ih}))$$

$$= \sum_i \sum_j p_i^T C_{ij} p_j + \sum_{ij} p_{ij} u_{ij} - \sum_i \log \sum_h \exp(u_{ih})$$

Differentiable

$$L(p, u) = \sum_i \sum_j p_i^T C_{ij} p_j + \sum_{ij} p_{ij} u_{ij} - \sum_i \log \sum_h \exp(u_{ih})$$

$$\frac{\partial L(p, u)}{\partial p_i} = 0, \quad \frac{\partial L(p, u)}{\partial u_{ij}} = 0$$

$$L(p, u) = \sum_i \sum_j p_i^T C_{ij} p_j + \sum_{ij} p_{ij} u_{ij} - \sum_i \log \sum_h \exp(u_{ih})$$

$j \neq i$

$$\frac{\partial L(p, u)}{\partial p_i} = 0 \Rightarrow u_i = - \sum_j C_{ij} p_j$$

M step

$j \neq i$

$$L(p, u) = \sum_i \sum_j p_i^T C_{ij} p_j + \sum_i p_i^T u_i - \sum_i \log \sum_h \exp(u_{ih})$$

$$\frac{\partial L(p, u)}{\partial u_{ij}} = 0 \Rightarrow p_{ij} = \frac{\exp(u_{ij})}{\sum_h \exp(u_{ih})},$$

Expectation step

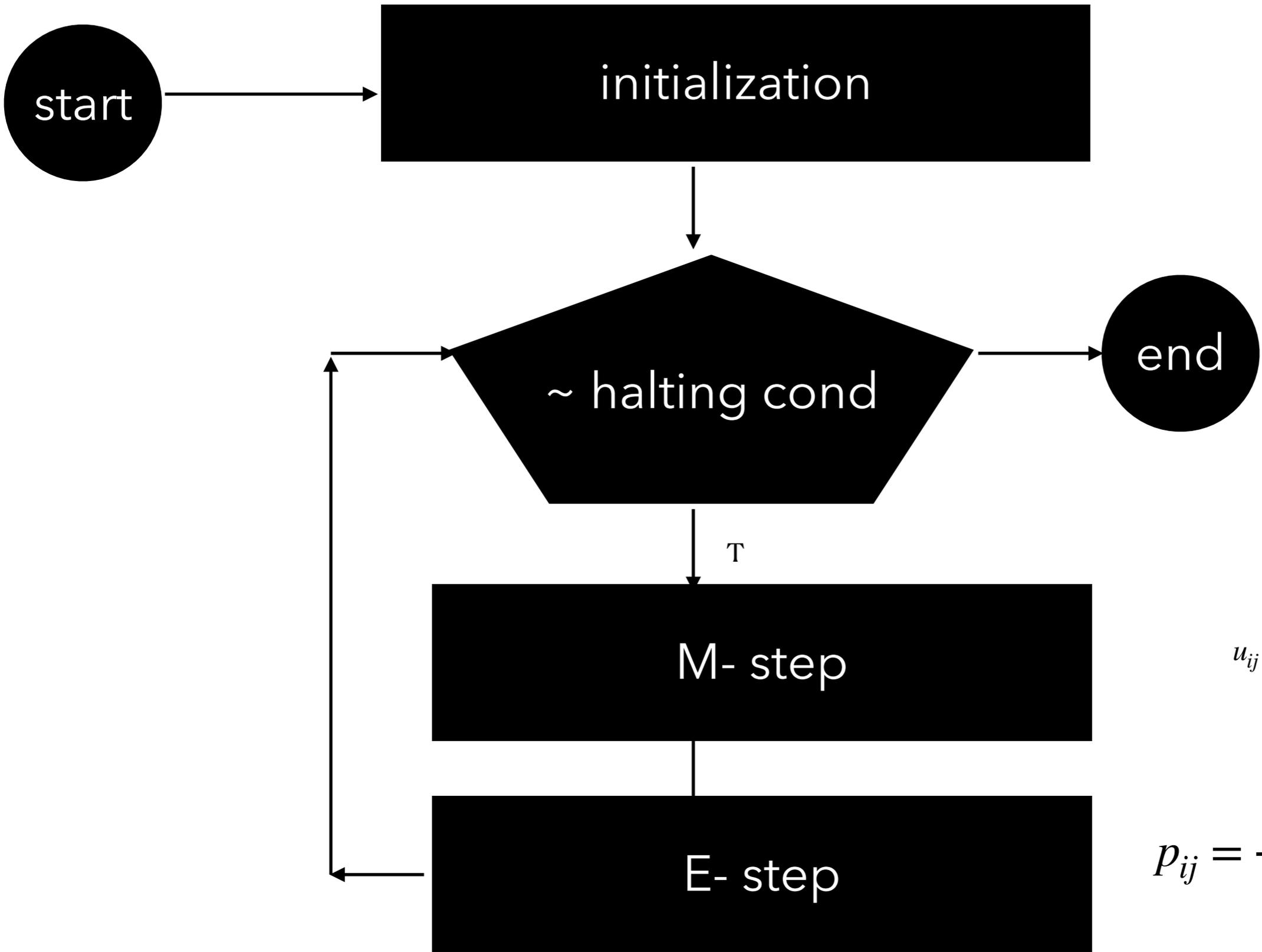
Thermal equilibrium

$$u_{ij} = - \sum_j C_{ij} p_{ij}$$

Maximization step

$$p_{ij} = \frac{\exp(u_{ij})}{\sum_h \exp(u_{ih})},$$

Expectation step



$$u_{ij} = - \sum_j C_{ij} p_{ij}$$

$$p_{ij} = \frac{\exp(u_{ij})}{\sum_h \exp(u_{ih})}$$

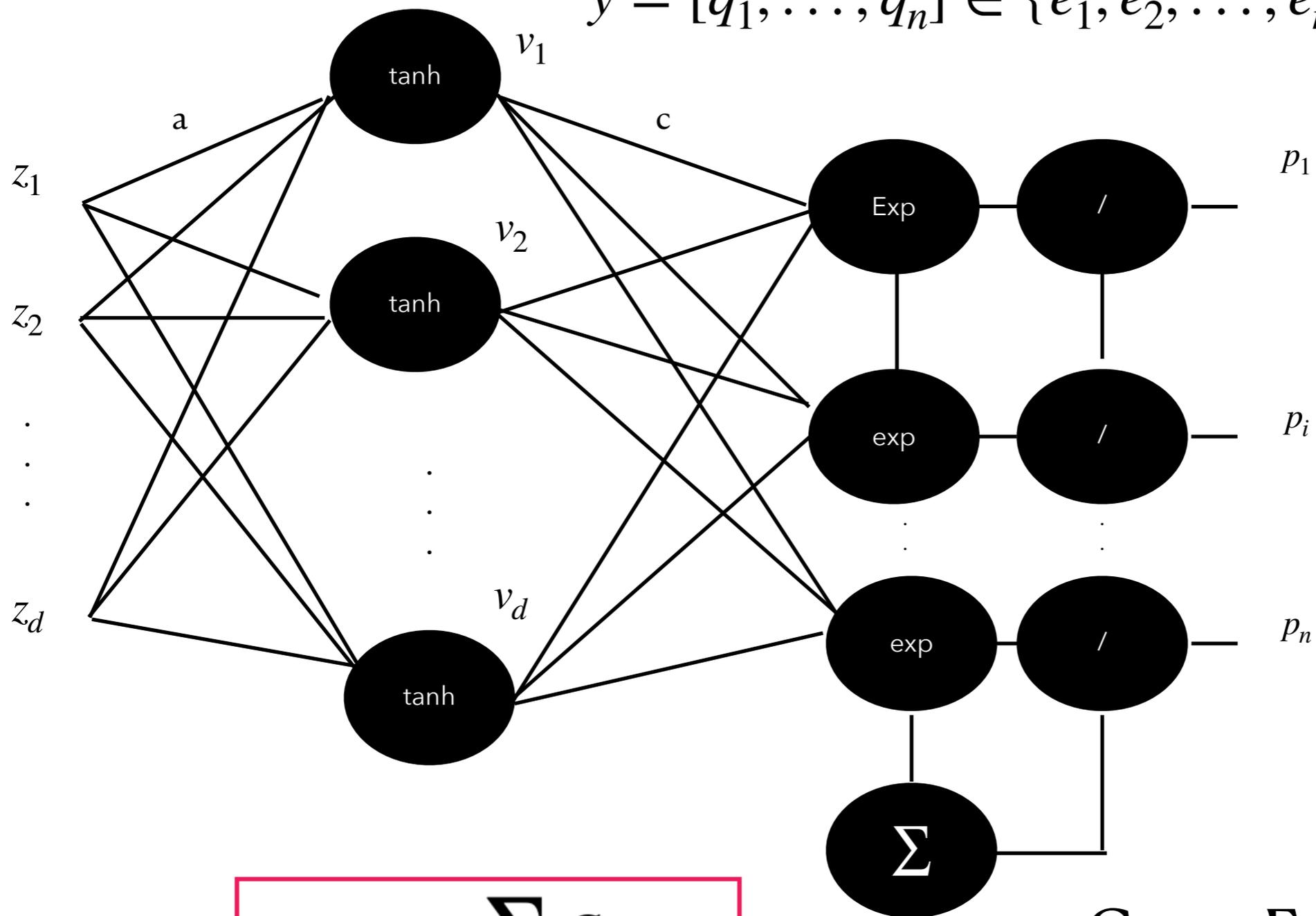
Classification neural network

$$h_j = \sum_{k=1}^d a_{jk} v_k \quad v = [v_1, \dots, v_d]$$

$$v_j = \tanh(h_j)$$

$$u_i = - \sum_j C_{ij} v_j$$
$$p_{ij} = \frac{\exp(u_{ij})}{\sum_h \exp(u_{ih})}$$

$$y = [q_1, \dots, q_n] \in \{e_1, e_2, \dots, e_n\}$$



$$u_i = - \sum_j C_{ij} v_j$$

$$p_i = \frac{\exp(u_i)}{\sum_h \exp(u_h)}$$

Cross Entropy,
softmaxloss

$$Q(q || p) = \sum_i q_i \ln \frac{q_i}{p_i}$$

Let $y = e_b$. Find

1. $\frac{dQ}{du_i} = ? \text{ for } i = b$

2. $\frac{dQ}{du_i} = ? \text{ for } i \neq b$

3. $\frac{dQ}{da_{jk}} = ?$