

# Neural networks

Conditional random fields - computing marginals

# INFERENCE

**Topics:** computing  $p(\mathbf{y}|\mathbf{X})$

- Then we have:

$$p(\mathbf{y}|\mathbf{X}) = \exp \left( \sum_{k=1}^K a_u(y_k) + \sum_{k=1}^{K-1} a_p(y_k, y_{k+1}) \right) / Z(\mathbf{X})$$

where

$$Z(\mathbf{X}) = \sum_{y'_1} \sum_{y'_2} \cdots \sum_{y'_K} \exp \left( \sum_{k=1}^K a_u(y'_k) + \sum_{k=1}^{K-1} a_p(y'_k, y'_{k+1}) \right)$$

hard to compute



# INFERENCE

**Topics:** forward/backward or belief propagation

- Computing both tables is often referred to as the forward/backward algorithm for CRFs
  - $\alpha$  is computed with a forward pass
  - $\beta$  is computed with a backward pass
- It has other names
  - belief propagation
  - sum-product
- $\alpha$  gives the summation from the left
- $\beta$  gives the summation from the right



# INFERENCE

**Topics:** computing  $p(y_k|\mathbf{X})$ ,  $p(y_k, y_{k+1}|\mathbf{X})$

- The  $\alpha / \beta$  tables can be used to compute marginals

$$p(y_k|\mathbf{X}) = \frac{\exp(a_u(y_k) + \log \alpha_{k-1}(y_k) + \log \beta_{k+1}(y_k))}{\sum_{y'_k} \exp(a_u(y'_k) + \log \alpha_{k-1}(y'_k) + \log \beta_{k+1}(y'_k))}$$

$$p(y_k, y_{k+1}|\mathbf{X}) = \frac{\exp \left( \begin{array}{l} a_u(y_k) + a_p(y_k, y_{k+1}) + a_u(y_{k+1}) \\ + \log \alpha_{k-1}(y_k) + \log \beta_{k+2}(y_{k+1}) \end{array} \right)}{\sum_{y'_k} \sum_{y'_{k+1}} \exp \left( \begin{array}{l} a_u(y'_k) + a_p(y'_k, y'_{k+1}) + a_u(y'_{k+1}) \\ + \log \alpha_{k-1}(y'_k) + \log \beta_{k+2}(y'_{k+1}) \end{array} \right)}$$