

Neural networks

Conditional random fields - performing classification

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

- The α / β tables can be used to compute marginals

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

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

CLASSIFICATION

Topics: making a prediction (option 1)

- At each position k , pick label y_k with highest marginal probability $p(y_k|\mathbf{X})$
 - this choice is the one that minimizes the sum of the classification errors over the whole sequence, assuming the CRF is the true distribution

$$\min_{\mathbf{y}^*} \mathbb{E} \left[\sum_k 1_{y_k \neq y_k^*} \right]$$

$$\begin{aligned} & \min_{\mathbf{y}^*} \mathbb{E} \left[\sum_k 1_{y_k \neq y_k^*} \right] \\ = & \min_{\mathbf{y}^*} \sum_{y_1} \cdots \sum_{y_K} \left(\sum_k 1_{y_k \neq y_k^*} \right) p(\mathbf{y} | \mathbf{X}) \end{aligned}$$

$$\begin{aligned}
& \min_{\mathbf{y}^*} \mathbb{E} \left[\sum_k 1_{y_k \neq y_k^*} \right] \\
= & \min_{\mathbf{y}^*} \sum_{y_1} \cdots \sum_{y_K} \left(\sum_k 1_{y_k \neq y_k^*} \right) p(\mathbf{y} | \mathbf{X}) \\
= & \min_{y_1^*} \dots \min_{y_K^*} \underbrace{\sum_{y_1}}_{\quad} \cdots \underbrace{\sum_{y_K}}_{\quad} \underbrace{\left(\sum_k 1_{y_k \neq y_k^*} \right)}_{\quad} p(\mathbf{y} | \mathbf{X})
\end{aligned}$$

$$\begin{aligned}
& \min_{\mathbf{y}^*} \mathbb{E} \left[\sum_k 1_{y_k \neq y_k^*} \right] \\
&= \min_{\mathbf{y}^*} \sum_{y_1} \cdots \sum_{y_K} \left(\sum_k 1_{y_k \neq y_k^*} \right) p(\mathbf{y} | \mathbf{X}) \\
&= \min_{y_1^*} \dots \min_{y_K^*} \sum_{y_1} \cdots \sum_{y_K} \left(\sum_k 1_{y_k \neq y_k^*} \right) p(\mathbf{y} | \mathbf{X}) \\
&= \min_{y_1^*} \dots \min_{y_K^*} \sum_k \sum_{y_1} \cdots \sum_{y_K} 1_{y_k \neq y_k^*} p(\mathbf{y} | \mathbf{X})
\end{aligned}$$

$$\begin{aligned}
& \min_{\mathbf{y}^*} \mathbb{E} \left[\sum_k 1_{y_k \neq y_k^*} \right] \\
&= \min_{\mathbf{y}^*} \sum_{y_1} \cdots \sum_{y_K} \left(\sum_k 1_{y_k \neq y_k^*} \right) p(\mathbf{y} | \mathbf{X}) \\
&= \min_{y_1^*} \dots \min_{y_K^*} \sum_{y_1} \cdots \sum_{y_K} \left(\sum_k 1_{y_k \neq y_k^*} \right) p(\mathbf{y} | \mathbf{X}) \\
&= \min_{y_1^*} \dots \min_{y_K^*} \sum_k \sum_{y_1} \cdots \sum_{y_K} 1_{y_k \neq y_k^*} p(\mathbf{y} | \mathbf{X}) \\
&= \min_{y_1^*} \dots \min_{y_K^*} \sum_k \sum_{y_k} 1_{y_k \neq y_k^*} \sum_{y_1} \cdots \sum_{y_{k-1}} \sum_{y_{k+1}} \sum_{y_K} p(\mathbf{y} | \mathbf{X})
\end{aligned}$$

$$\begin{aligned}
& \min_{\mathbf{y}^*} \mathbb{E} \left[\sum_k 1_{y_k \neq y_k^*} \right] \\
&= \min_{\mathbf{y}^*} \sum_{y_1} \cdots \sum_{y_K} \left(\sum_k 1_{y_k \neq y_k^*} \right) p(\mathbf{y} | \mathbf{X}) \\
&= \min_{y_1^*} \dots \min_{y_K^*} \sum_{y_1} \cdots \sum_{y_K} \left(\sum_k 1_{y_k \neq y_k^*} \right) p(\mathbf{y} | \mathbf{X}) \\
&= \min_{y_1^*} \dots \min_{y_K^*} \sum_k \sum_{y_1} \cdots \sum_{y_K} 1_{y_k \neq y_k^*} p(\mathbf{y} | \mathbf{X}) \\
&= \min_{y_1^*} \dots \min_{y_K^*} \sum_k \sum_{y_k} 1_{y_k \neq y_k^*} \sum_{y_1} \cdots \sum_{y_{k-1}} \sum_{y_{k+1}} \sum_{y_K} p(\mathbf{y} | \mathbf{X}) \\
&= \min_{y_1^*} \dots \min_{y_K^*} \sum_k \sum_{y_k} 1_{y_k \neq y_k^*} p(y_k | \mathbf{X})
\end{aligned}$$

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& \min_{\mathbf{y}^*} \mathbb{E} \left[\sum_k 1_{y_k \neq y_k^*} \right] \\
&= \min_{\mathbf{y}^*} \sum_{y_1} \cdots \sum_{y_K} \left(\sum_k 1_{y_k \neq y_k^*} \right) p(\mathbf{y} | \mathbf{X}) \\
&= \min_{y_1^*} \dots \min_{y_K^*} \sum_{y_1} \cdots \sum_{y_K} \left(\sum_k 1_{y_k \neq y_k^*} \right) p(\mathbf{y} | \mathbf{X}) \\
&= \min_{y_1^*} \dots \min_{y_K^*} \sum_k \sum_{y_1} \cdots \sum_{y_K} 1_{y_k \neq y_k^*} p(\mathbf{y} | \mathbf{X}) \\
&= \min_{y_1^*} \dots \min_{y_K^*} \sum_k \sum_{y_k} 1_{y_k \neq y_k^*} \sum_{y_1} \cdots \sum_{y_{k-1}} \sum_{y_{k+1}} \sum_{y_K} p(\mathbf{y} | \mathbf{X}) \\
&= \min_{y_1^*} \dots \min_{y_K^*} \sum_k \sum_{y_k} 1_{y_k \neq y_k^*} p(y_k | \mathbf{X}) \\
&= \min_{y_1^*} \left(\sum_{y_1} 1_{y_1 \neq y_1^*} p(y_1 | \mathbf{X}) \right) + \cdots + \min_{y_K^*} \left(\sum_{y_K} 1_{y_K \neq y_K^*} p(y_K | \mathbf{X}) \right)
\end{aligned}$$

$$\begin{aligned}
& \min_{\mathbf{y}^*} \mathbb{E} \left[\sum_k 1_{y_k \neq y_k^*} \right] \\
&= \min_{\mathbf{y}^*} \sum_{y_1} \cdots \sum_{y_K} \left(\sum_k 1_{y_k \neq y_k^*} \right) p(\mathbf{y}|\mathbf{X}) \\
&= \min_{y_1^*} \dots \min_{y_K^*} \sum_{y_1} \cdots \sum_{y_K} \left(\sum_k 1_{y_k \neq y_k^*} \right) p(\mathbf{y}|\mathbf{X}) \\
&= \min_{y_1^*} \dots \min_{y_K^*} \sum_k \sum_{y_1} \cdots \sum_{y_K} 1_{y_k \neq y_k^*} p(\mathbf{y}|\mathbf{X}) \\
&= \min_{y_1^*} \dots \min_{y_K^*} \sum_k \sum_{y_k} 1_{y_k \neq y_k^*} \sum_{y_1} \cdots \sum_{y_{k-1}} \sum_{y_{k+1}} \sum_{y_K} p(\mathbf{y}|\mathbf{X}) \\
&= \min_{y_1^*} \dots \min_{y_K^*} \sum_k \sum_{y_k} 1_{y_k \neq y_k^*} p(y_k|\mathbf{X}) \\
&= \min_{y_1^*} \left(\sum_{y_1} 1_{y_1 \neq y_1^*} p(y_1|\mathbf{X}) \right) + \cdots + \min_{y_K^*} \left(\sum_{y_K} 1_{y_K \neq y_K^*} p(y_K|\mathbf{X}) \right) \\
&= \min_{y_1^*} (1 - p(y_1^*|\mathbf{X})) + \cdots + \min_{y_K^*} (1 - p(y_K^*|\mathbf{X}))
\end{aligned}$$

$$\begin{aligned}
& \min_{\mathbf{y}^*} \mathbb{E} \left[\sum_k 1_{y_k \neq y_k^*} \right] \\
&= \min_{\mathbf{y}^*} \sum_{y_1} \cdots \sum_{y_K} \left(\sum_k 1_{y_k \neq y_k^*} \right) p(\mathbf{y}|\mathbf{X}) \\
&= \min_{y_1^*} \dots \min_{y_K^*} \sum_{y_1} \cdots \sum_{y_K} \left(\sum_k 1_{y_k \neq y_k^*} \right) p(\mathbf{y}|\mathbf{X}) \\
&= \min_{y_1^*} \dots \min_{y_K^*} \sum_k \sum_{y_1} \cdots \sum_{y_K} 1_{y_k \neq y_k^*} p(\mathbf{y}|\mathbf{X}) \\
&= \min_{y_1^*} \dots \min_{y_K^*} \sum_k \sum_{y_k} 1_{y_k \neq y_k^*} \sum_{y_1} \cdots \sum_{y_{k-1}} \sum_{y_{k+1}} \sum_{y_K} p(\mathbf{y}|\mathbf{X}) \\
&= \min_{y_1^*} \dots \min_{y_K^*} \sum_k \sum_{y_k} 1_{y_k \neq y_k^*} p(y_k|\mathbf{X}) \\
&= \min_{y_1^*} \left(\sum_{y_1} 1_{y_1 \neq y_1^*} p(y_1|\mathbf{X}) \right) + \cdots + \min_{y_K^*} \left(\sum_{y_K} 1_{y_K \neq y_K^*} p(y_K|\mathbf{X}) \right) \\
&= \min_{y_1^*} (1 - p(y_1^*|\mathbf{X})) + \cdots + \min_{y_K^*} (1 - p(y_K^*|\mathbf{X})) \\
&= 1 - \max_{y_1^*} p(y_1^*|\mathbf{X}) + \cdots + 1 - \max_{y_K^*} p(y_K^*|\mathbf{X})
\end{aligned}$$

CLASSIFICATION

Topics: making a prediction (option 2)

- Find most probable prediction:

$$\arg \max_{\mathbf{y}^*} p(\mathbf{y}|\mathbf{X})$$

- A Viterbi decoding algorithm can be used for that
 - ▶ forward pass: replace $\log \sum_{y'_k} \exp(\cdot)$ by $\max_{y'_k} (\cdot)$ and fill the table
 - ▶ backward pass: starting from the maximal value y_K^* at the last position, follow the backward trace of the max operations to decode the maximizing sequence

CLASSIFICATION

Topics: making a prediction (option 2)

nb. of classes

Complexity in $O(KC^2)$

• Algorithm goes as follows:

▶ initialize, for all values of y'_2 :

- $\alpha_1^*(y'_2) \Leftarrow \max_{y'_1} a_u(y'_1) + a_p(y'_1, y'_2)$
- $\alpha_1^\leftarrow(y'_2) \Leftarrow \arg \max_{y'_1} a_u(y'_1) + a_p(y'_1, y'_2)$

▶ for $k = 2$ to $K-1$, for all values of y'_{k+1} :

- $\alpha_k^*(y'_{k+1}) \Leftarrow \max_{y'_k} a_u(y'_k) + a_p(y'_k, y'_{k+1}) + \alpha_{k-1}^*(y'_k)$
- $\alpha_k^\leftarrow(y'_{k+1}) \Leftarrow \arg \max_{y'_k} a_u(y'_k) + a_p(y'_k, y'_{k+1}) + \alpha_{k-1}^*(y'_k)$

▶ $\max_{\mathbf{y}^*} p(\mathbf{y}|\mathbf{X}) \Leftarrow \max_{y'_K} a_u(y'_K) + \alpha_{K-1}^*(y'_K)$

▶ $y_K^* \Leftarrow \arg \max_{y'_K} a_u(y'_K) + \alpha_{K-1}^*(y'_K)$ } backward decoding

▶ for $k = K-1$ to 1 : $y_k^* \Leftarrow \alpha_k^\leftarrow(y_{k+1}^*)$