TTIC 31230, Fundamentals of Deep Learning

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Connectionist Temporal Classification (CTC)

Connectionist Temporal Classification (CTC) A Successful Deep Latent Variable Model

A speech signal

$$x = x_1, \ldots, x_T$$

is labeled with a phone sequence

$$y = y_1, \dots, y_N$$

with $N \ll T$ and with $y_n \in \mathcal{P}$ for a set of phonemes \mathcal{P} .

The length N of y is not determined by x and the alignment between x and y is not given.

The CTC Model

$$P_{\Phi}(y|x) = \sum_{z} P_{\Phi}(z|x) P_{\Phi}(y|z).$$

Input Signal: $x = x_1, \ldots, x_T$

Latent Label: $z = z_1, \ldots, z_T, z_t \in \mathcal{P} \cup \{\bot\}$

Output: $y(z) = y_1, \ldots, y_N$ $N \ll T$

y(z) is the result of removing all the occurrences of \perp from z:

$$z \Rightarrow y$$

$$\perp$$
, a_1 , \perp , \perp , \perp , \perp , a_2 , \perp , \perp , a_3 , \perp \Rightarrow a_1 , a_2 , a_3

The CTC Model

For $z \in \mathcal{P} \cup \{\bot\}$ we have an embedding e(z). The embedding is a parameter of the model.

$$h_1, \ldots, h_T = \text{RNN}_{\Phi}(x_1, \ldots, x_T)$$

$$P_{\Phi}(z_t|x_1,\ldots,x_T) = \underset{z}{\text{softmax}} e(z)^{\top} h_t$$

 $z_1, \ldots z_T$ are all independent given x.

Dynamic Programming

$$x = x_1, \ldots, x_T$$

 $z = z_1, \ldots, z_T, z_t \in \mathcal{P} \cup \{\bot\}$
 $y = y_1, \ldots, y_N, y_n \in \mathcal{P}, N << T$
 $y(z) = (z_1, \ldots, z_T) - \bot$

$$\vec{y_t} = (z_1, \dots, z_t) - \bot$$

 $F[n, t] = P(\vec{y_t} = y_1, \dots, y_n)$
 $P(y) = F[N, T]$

Dynamic Programming

$$\vec{y_t} = (z_1, \dots, z_t) - \bot$$

 $F[n, t] = P(\vec{y_t} = y_1, \dots, y_n)$

$$F[0,0] = 1$$

For $n = 1, ..., N$ $F[n,0] = 0$
For $t = 1, ..., T$
 $F[0,t] = P(z_t = \bot)F[0,t-1]$
for $n = 1, ..., N$
 $F[n,t] = P(z_t = \bot)F[n,t-1] + P(z_t = y_n)F[n-1,t-1]$

Back-Propagation

$$\mathcal{L} = -\ln F[N, T]$$

We can now back-propagate through this computation.

\mathbf{END}