# Connectionist Temporal Classification

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## Problem representation(1)

Sequence to sequence learning
Unsegmented real-valued input stream -> Discrete label sequence

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Sequence to sequence learning

Unsegmented real-valued input stream -> Discrete label sequence

- -- Classification
- -- Temporal Classification
- -- Connectionist Temporal Classification, as loss function

## Problem representation(2)

```
Input: X = [x_1, x_2, ..., x_T], x_n \in \mathbb{R}^m

Output: Z = [z_1, z_2, ..., z_U], z_m \in L, L is a set of finite labels h(X) = Z
```

-- input: unsegmented vs. discrete

Morse: 122 1 -> we(discrete, segmented)

Speech: waveform of /lnv'nplid3/ -> love knowledge(discrete, unseg)

## Basic network settings for classification

Input

Output

FNN/CNN/RNN

LSTM(Long short-term memory)

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Output:  $Z = [z_1, z_2, ..., z_U], z_U \in L$ , L is a set of finite **phone** labels

DNN: h(X) = Z

-- T vs. U, at least in Speech Recognition

 $U \leq T$ 

uncrossed

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DNN:  $f(X) = \pi$ ,  $\pi$  is a label sequence of length T

Map:  $\beta(\pi) = \pi^* = Z$ , egs,  $\beta(a - ab - b) = \beta(-aa - abb) = aab$ 

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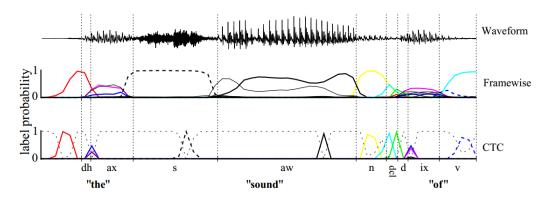
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-- The symbol "-" means nothing is output, that is, **blank**.

Doesn't mean it doesn't contribute, but accumulating, then **spike**.



#### **Propagate**

-- probability to generate **any** sequence  $\pi$ 

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#### **Feedforward**

-- select **some** sequence with biggest probability

$$h(\mathbf{x}) = \arg \max_{\mathbf{l} \in L \le T} p(\mathbf{l}|\mathbf{x})$$

### **Backpropagate**

-- probability to generate a **specific** sequence **l**, to be **maximized** 

$$p(\mathbf{l}|\mathbf{x}) = \sum_{\pi \in \mathcal{B}^{-1}(\mathbf{l})} p(\pi|\mathbf{x})$$

#### **Backpropagate**

-- calculate it first, using Forward-Backward algorithm

$$p(\mathbf{l}|\mathbf{x}) = \sum_{\pi \in \mathcal{B}^{-1}(\mathbf{l})} p(\pi|\mathbf{x})$$

-- maximize likelihood minimize -log of it, using **Gradient Descent** algorithm

$$O^{ML}(S, \mathcal{N}_w) = -\sum_{(\mathbf{x}, \mathbf{z}) \in S} ln(p(\mathbf{z}|\mathbf{x}))$$

## Finally

select **some** sequence with biggest probability -- search problem, using **Prefix search** etc.

$$h(\mathbf{x}) = \arg \max_{\mathbf{l} \in L^{\leq T}} p(\mathbf{l}|\mathbf{x})$$

#### Reference

Graves, Alex, et al. "Connectionist temporal classification: labelling unsegmented sequence data with recurrent neural networks." *Proceedings of the 23rd international conference on Machine learning.* ACM, 2006.

Thanks.