End-to-end systems: Deep Speech and CTC

Steve Renals

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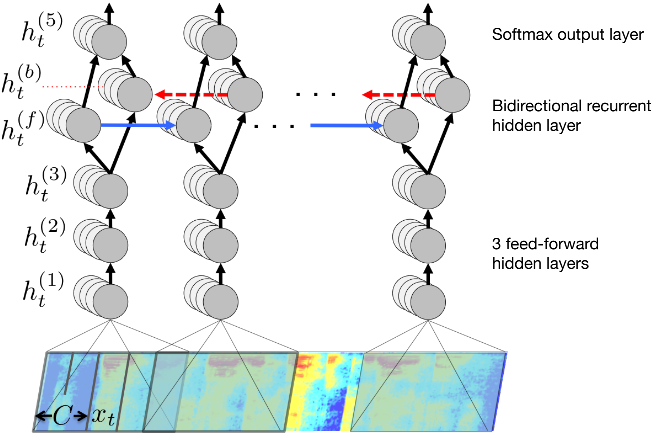
End-to-end systems

- End-to-end systems are systems which learn to directly map from an input sequence X to an output sequence Y, estimating $P(Y|X)$
- ML trained HMMs are kind of end-to-end system – the HMM estimates $P(X|Y)$ but when combined with a language model gives an estimate of $P(Y|X)$
- Sequence discriminative training of HMMs (using GMMs or DNNs) can be regarded as end-to-end
  - But training is quite complicated – need to estimate the denominator (total likelihood) using lattices, first train conventionally (ML for GMMs, CE for NNs) then finetune using sequence discriminative training
  - Lattice-free MMI is one way to address these issues
- Other approaches based on recurrent networks which directly map input to output sequences
  - CTC – Connectionist Temporal Classification
  - Encoder-decoder approaches

Deep Speech

Output: character probabilities (a-z, <apostrophe>, <space>, <blank>)
Trained using CTC



Input: Filter bank features (spectrogram)

Hannun et al, “Deep Speech: Scaling up end-to-end speech recognition”, https://arxiv.org/abs/1412.5567.

Deep Speech: Results

Model	SWB	CH	Full
Vesely et al. (GMM-HMM BMMI) [44]	18.6	33.0	25.8
Vesely et al. (DNN-HMM sMBR) [44]	12.6	24.1	18.4
Maas et al. (DNN-HMM SWB) [28]	14.6	26.3	20.5
Maas et al. (DNN-HMM FSH) [28]	16.0	23.7	19.9
Seide et al. (CD-DNN) [39]	16.1	n/a	n/a
Kingsbury et al. (DNN-HMM sMBR HF) [22]	13.3	n/a	n/a
Sainath et al. (CNN-HMM) [36]	11.5	n/a	n/a
Soltau et al. (MLP/CNN+I-Vector) [40]	**10.4**	n/a	n/a
Deep Speech SWB	20.0	31.8	25.9
Deep Speech SWB + FSH	12.6	**19.3**	**16.0**

Table 3: Published error rates (%WER) on Switchboard dataset splits. The columns labeled "SWB" and "CH" are respectively the easy and hard subsets of Hub5'00.

Deep Speech Training

- Maps from acoustic frames to character sequences
- CTC loss function
- Makes good use of large training data
    - Synthetic additional training data by jittering the signal and adding noise
- Many computational optimisations
- n-gram language model to impose word-level constraints
- Competitive results on standard tasks

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Connectionist Temporal Classification (CTC)

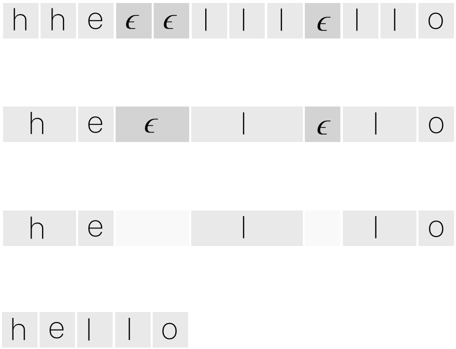
- Train a recurrent network to map from input sequence X to output sequence Y
  - sequences can be different lengths
  - frame-level alignment (matching each input frame to an output token) not required
- CTC sums over all possible alignments (similar to forward-backward algorithm) – "alignment free"
- Possible to back-propagate gradients through CTC

This presentation of CTC based on Awni Hannun, "Sequence Modeling with CTC", *Distill*. https://distill.pub/2017/ctc

CTC: Alignment

- Imagine mapping $(x_1, x_2, x_3, x_4, x_5, x_6)$ to $[a, b, c]$
- Possible alignments: *aaabbc*, *aabbcc*, *abbbbc*, ...
- However
  - Don't always want to map every input frame to an output symbol (e.g.silence)
  - Want to be able to have two identical symbols adjacent to each other e.g. $[h, e, l, l, o]$
- Solve this with an additional *blank* symbol (ϵ)
  - Blanks removed from the output sequence
  - To model the same character in a row, separate with a blank

CTC: Alignment example



First, merge repeat characters.

Then, remove any ϵ tokens.

The remaining characters are the output.

CTC: Valid and invalid alignments

Consider an output [c, a, t] with an input of length six

Valid Alignments	Invalid Alignments	
ϵ c c ϵ a t	c ϵ c ϵ a t	corresponds to $Y =$ [c, c, a, t]
c c a a t t	c c a a t	has length 5
c a ϵ ϵ ϵ t	c ϵ ϵ ϵ t t	missing the 'a'

CTC: Alignment properties

- Monotonic – Alignments are monotonic (left-to-right model); no re-ordering (unlike neural machine translation)
- Many-to-one – Alignments are many-to-one; many inputs can map to the same output (however many outputs cannot map to a single input)
- CTC doesn't find a single alignment, sums over all possible alignments

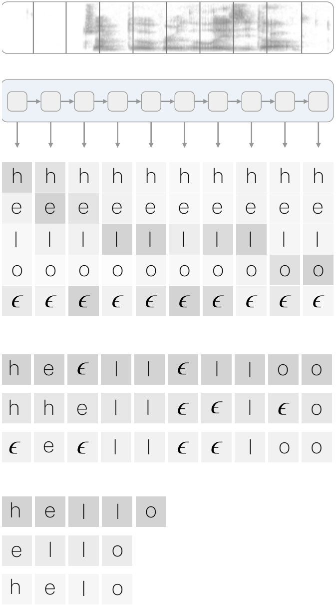
CTC: Loss function

$$P(Y|X) = \sum_A \prod_t p(a_t|X)$$

Estimate using an RNN

Sum over alignments using dynamic programming – similar structure as used in forward-backward algorithm and Viterbi

CTC: Distribution over alignments



We start with an input sequence, like a spectrogram of audio.

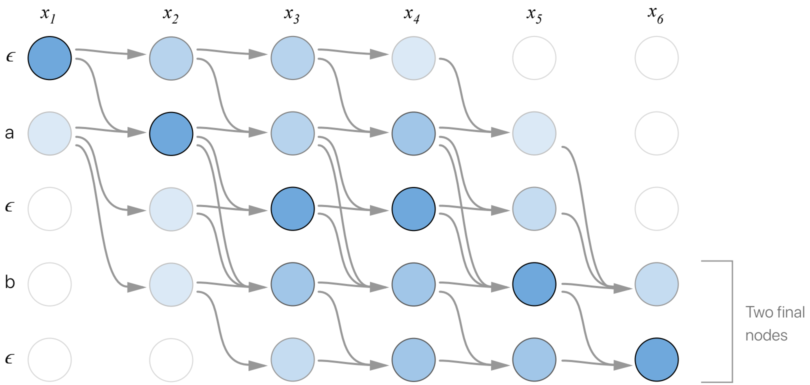
The input is fed into an RNN, for example.

The network gives $p_t(a \mid X)$, a distribution over the outputs {h, e, l, o, ϵ} for each input step.

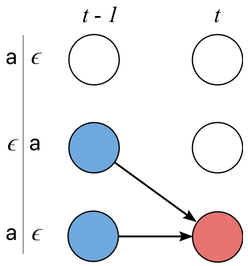
With the per time-step output distribution, we compute the probability of different sequences

By marginalizing over alignments, we get a distribution over outputs.

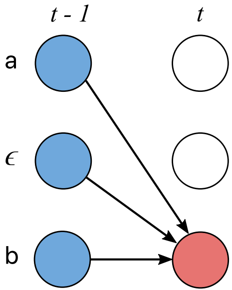
CTC: Valid paths



CTC: Allowed transitions



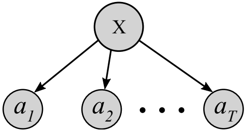
No skip transition allowed
Previous token in output seq
OR blank between repeat symbols



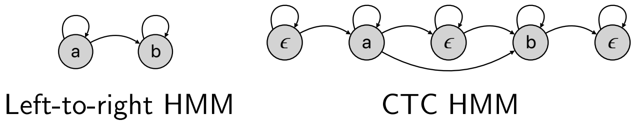
Skip transition allowed
Previous token is a blank between different symbols

Understanding CTC: Conditional independence assumption

- Each output is dependent on the entire input sequence (in Deep Speech this is achieved using a bidirectional recurrent layer)
- Given the inputs, each output is independent of the other outputs (conditional independence)
- CTC does not learn a language model over the outputs, although a language model can be applied later
- Graphical model showing dependences in CTC:



Understanding CTC: CTC and HMM



- CTC can be interpreted as an HMM with additional (skippable) blank states, trained discriminatively

Mozilla Deep Speech

- Mozilla have released an Open Source TensorFlow implementation of the Deep Speech architecture:
- https://hacks.mozilla.org/2017/11/a-journey-to-10-word-error-rate/
- https://github.com/mozilla/DeepSpeech
- Close to state-of-the-art results on librispeech
- Mozilla Common Voice project: https://voice.mozilla.org/en

Summary and reading

- CTC is an alternative approach to sequence discriminative training, typically applied to RNN systems
- Used in "Deep Speech" architecture for end-to-end speech recognition
- Reading
  - A Hannun et al (2014), "Deep Speech: Scaling up end-to-end speech recognition", ArXiV:1412.5567. https://arxiv.org/abs/1412.5567
  - A Hannun (2017), "Sequence Modeling with CTC", *Distill*. https://distill.pub/2017/ctc