Deep Learning Audio

Lecture 3

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Outline

1. Automatic Speech Recognition (ASR)
2. Connectionist Temporal Classification (CTC)
3. Listen, Attend and Spell (LAS)

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ASR: Task definition

Mapping: signal $x(t) \rightarrow$ text sequence s

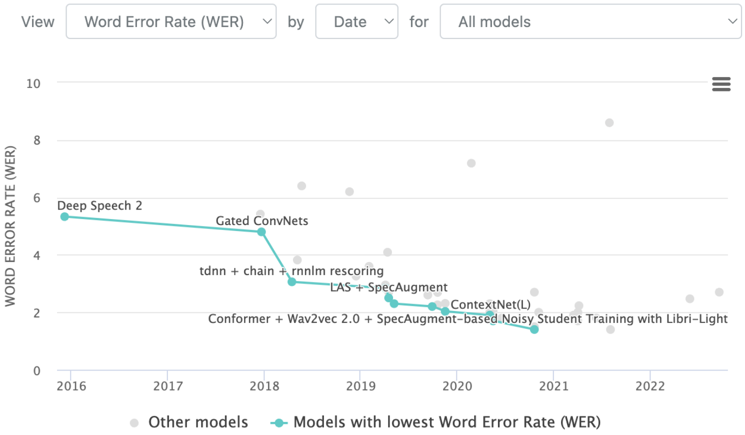


Figure: ASR progress for WER metric

ASR: Metrics

Word Error Rate

$$WER = \frac{S + D + I}{N} = \frac{S + D + I}{S + D + C}$$

- S - number of substitutions,
- D - number of deletions,
- I - number of insertions,
- C - number of correct words,
- N - number of words in the reference ($N = S + D + C$).

```
True: quick brown    fox jumped over a lazy dog
Pred: quick brow  an fox jumped over   lazy dog
```

Character Error Rate: same as WER, but for characters (WER is more important)

ASR: Datasets: LibriSpeech

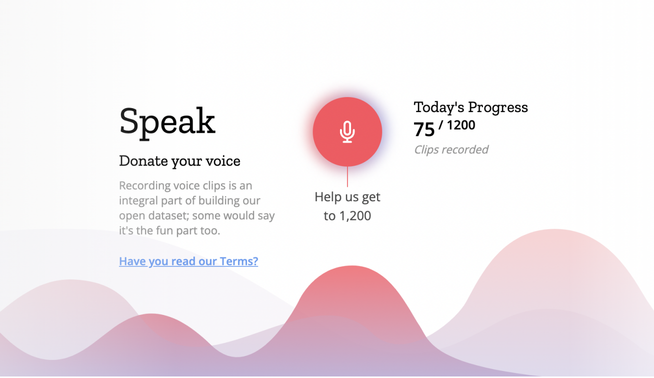
- 1,000 hours of audiobooks
- 10-20s audio, long sentences, complex language
- 'clean' (low-WER speakers) and 'other' (high-WER speakers) categories
- Human WER: test-clean: 5.83, test-other: 12.69
- Kaldi (2015) WER: test-clean: 8.01, test-other: 22.49
- Deep Speech 2 (2015) WER: test-clean: 5.15, test-other: 12.73

subset	hours	per-spk minutes	female spkrs	male spkrs	total spkrs
dev-clean	5.4	8	20	20	40
test-clean	5.4	8	20	20	40
dev-other	5.3	10	16	17	33
test-other	5.1	10	17	16	33
train-clean-100	100.6	25	125	126	251
train-clean-360	363.6	25	439	482	921
train-other-500	496.7	30	564	602	1166

Kaldi ASR by Daniel Povey

ASR: Datasets: Mozilla Common Voice

- Multiple languages
- Crowdsourced
- Simple language
- Short phrases
- Frequently updated and validated



Mozilla Common Voice

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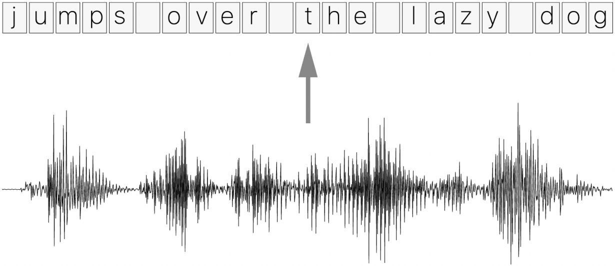
CTC: motivation

- Variable length input
- Variable length output
- No alignment
- Want a differentiable loss function to compute $P(Y|X)$ and $\arg\max P(Y|X)$



Sequence Modeling With CTC blog post

CTC: idea

- Split input into frames
- Classify each frame into letters classes
- Merge consecutive letters

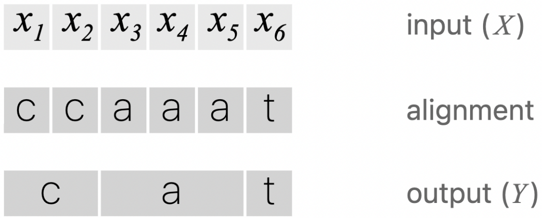


Figure: Example for [c, a ,t]

DeepSpeech 2

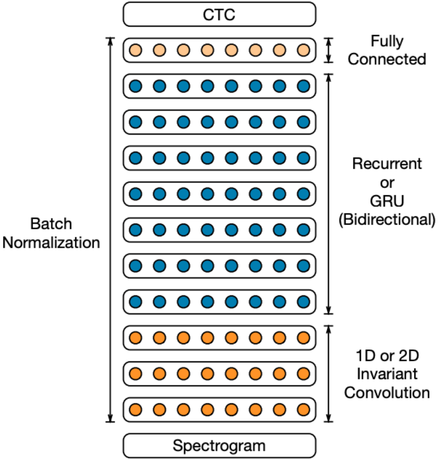


Figure: Deep Speech 2 architecture

Amodei, Dario Ananthanarayanan et al. (2015). Deep Speech 2: End-to-End Speech Recognition in English and Mandarin.

CTC: problems

Multiple consecutive letters (e.g.: hello), silence between words and letters.
Solution: add empty token ϵ

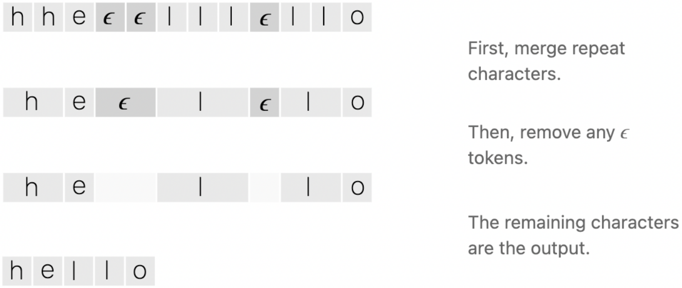


Figure: Example for [h, e, l, l, o]

CTC: Loss function

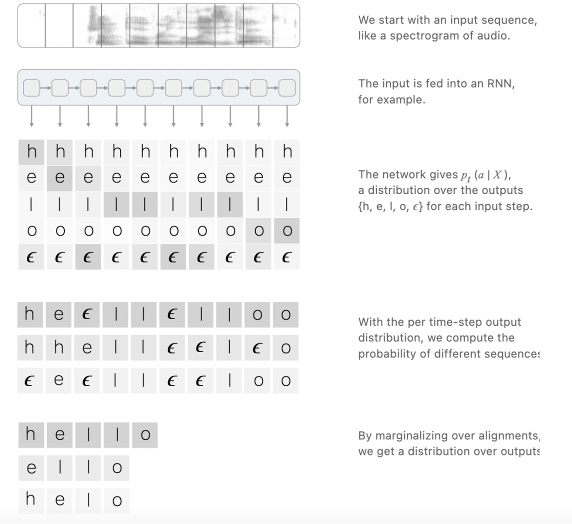


Figure: The CTC alignments give us a natural way to go from probabilities at each time-step to the probability of an output sequence.

CTC: Loss function

$$p(Y \mid X) \quad = \quad \sum_{A \in \mathcal{A}_{X,Y}} \quad \prod_{t=1}^{T} p_t(a_t \mid X)$$

The CTC conditional **probability**

marginalizes over the set of valid alignments

computing the **probability** for a single alignment step-by-step.

Figure: The CTC conditional probability

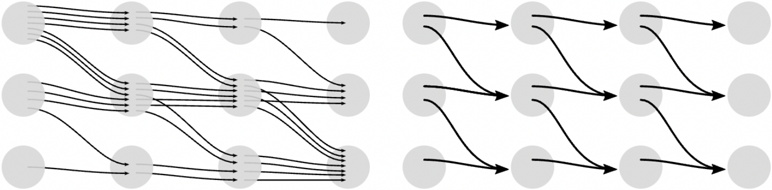


Figure: Summing over all alignments can be very expensive. Dynamic programming merges alignments, so it's much faster.

CTC: Computation

$$Z = [\epsilon,\ \overset{\text{a character}}{y_1},\ \epsilon,\ y_2,\ \ldots,\ \epsilon,\ y_U,\ \epsilon]$$

$\alpha_{s,t}$ is the CTC score of the subsequence $Z_{1:s}$ after t input steps.

Case 1

$$\alpha_{s,t} = (\alpha_{s-1,t-1} + \alpha_{s,t-1}) \cdot p_t(z_s \mid X)$$

The CTC probability of the two valid subsequences after $t-1$ input steps.

The probability of the current character at input step t.

Case 2

$$\alpha_{s,t} = (\alpha_{s-2,t-1} + \alpha_{s-1,t-1} + \alpha_{s,t-1}) \cdot p_t(z_s \mid X)$$

The CTC probability of the three valid subsequences after $t-1$ input steps.

The probability of the current character at input step t.

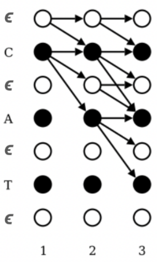


Figure: CTC computation with Dynamic programming

CTC: Properties

- Problem: Conditional Independence
- Example: "AAA". If predict 'A' as the first letter – suffix 'AA' should get much more probability than 'riple A'. If predict 't' first – the opposite.

Figure: Valid transcription could be "AAA" and "triple A".

- Advantage: Online – can be performed while the speaker is talking

CTC: Beam search

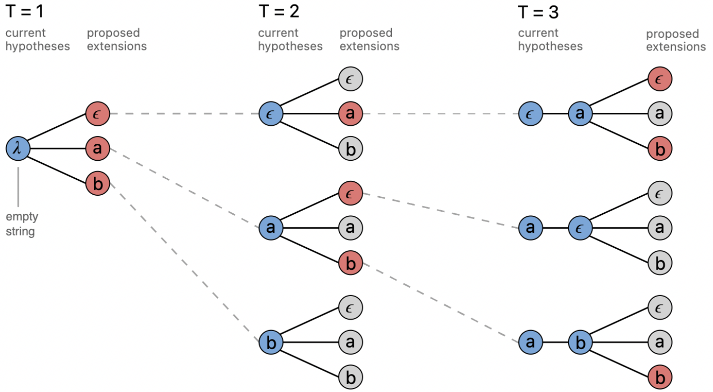


Figure: A standard beam search algorithm with an alphabet of $\{\epsilon, a, b\}$ and a beam size of 3.

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LAS: Architecture

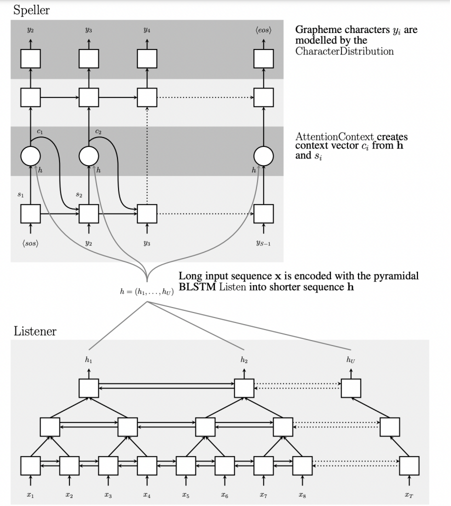

Figure: LAS model: **listener** – pyramidal BiLSTM encoding input sequence (spectrogram) into high level features h, **speller** – attention-based decoder generating the y characters from h. Train with cross entropy.

LAS: Beam search

- CTC computational cost T * beam size * **expand beam()**
- LAS computational cost T * beam size * **run decoder()**
- CTC usually uses 500 beam size, LAS – 3 beam size

WER: comparison

Method	**WER (test-clean)**	**WER (test-other)**
Human	5.83	12.69
Kaldi	8.01	22.49
Deep Speech 2	5.15	12.73
LAS	**3.2**	**9.8**