Language Independent End-to-End Architecture For Joint Language and Speech Recognition (2017)

Watanabe, S.; Hori, T.; Hershey, J.R.

Motivation / Goal

Recognize multiple languages at the same time

- Use a single model for 10 languages (EN, JP, CH, DE, ES, FR, IT, NL, PT, RU)
- Check if transfer learning between languages work
- Two tasks: identify language AND recognize speech (simultaneously)
- End to end: Directly train sequence to sequence, no lexicon, phoneme pronounciation maps, or manual alignment

Problems

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  $\rightarrow$ Spectral features of audio frames (e.g. in 10ms segments)

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  (a) word embeddings (word2vec) (would need fixed dictionary)
  (b) characters (one-hot)
    - Different char sets for languages (abc, äàąå, 漢字, , ひらがな)
    - Just unify all character sets (5500 total)

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- How to output language id?
  (a) separate one-hot output
  (b) as a special character: `[EN]Hello [CH] 你好`

Related Work

Related Work

- *Multilingual Speech Recognition With A Single End-To-End Model* (Shubham Toshniwal)
  - separate output for language id
  - only on 9 indian languages, hard to compare
- *Hybrid CTC/Attention Architecture for End-to-End Speech Recognition* (Watanabe et al. 2017)."
  - Same as this paper except only one language and more detailed

Model overview

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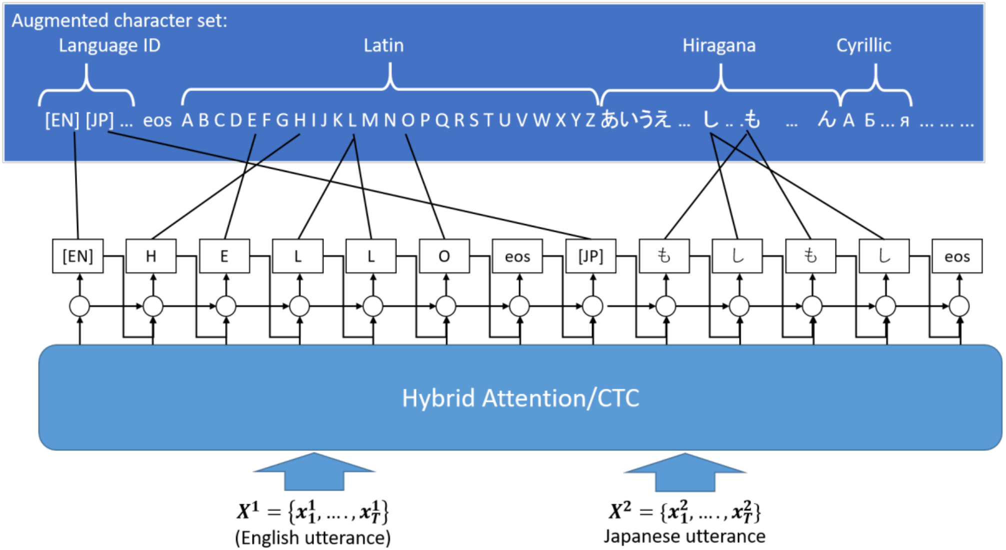


Augmented character set:
Language ID
Latin
Hiragana
Cyrillic
[EN] [JP] ... eos A B C D E F G H I J K L M N O P Q R S T U V W X Y Z あいうえ ... し .. .も ... ん А Б ... я ... ...
[EN]
H
E
L
L
O
eos
[JP]
も
し
も
し
eos
Hybrid Attention/CTC
$X^1 = \{x_1^1, \dots, x_T^1\}$
(English utterance)
$X^2 = \{x_1^2, \dots, x_T^2\}$
Japanese utterance

Simple Model overview

1. Input: for each audio frame one 2d input image, 3 channels (like RGB image processing)
2. Encoder
   - 2.1 VGGNet Convolutional NN (first 6 layers)
   - 2.2 One bidirectional LSTM layer
3. Decoder (Attention + one directional LSTM)
   - 3.1 Soft Attention for each input frame to each output character
   - 3.2 LSTM Layer
   - 3.3 Fully connected layer (per time step)
4. Output
   - N characters from union of all languages (one-hot / softmax)

Input

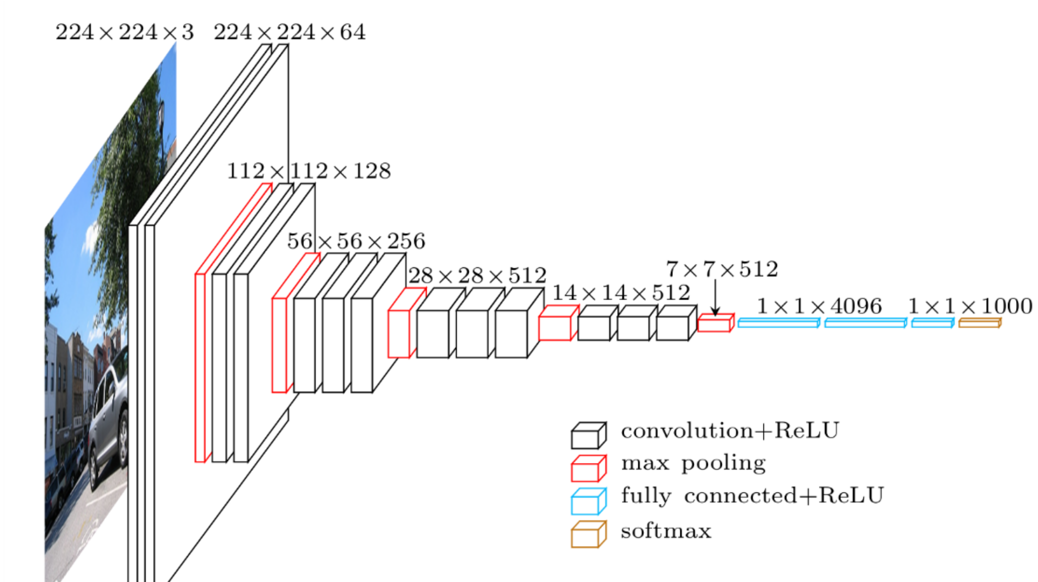
(Ab)use of image processing pipeline - input formatted like a RGB image

- first channel: spectral features
- second channel: delta spectral features
- third channel: deltadelta spectral features

"To use the same dimensional input features, we used 40-dimensional filterbank features with 3-dimensional pitch features implemented in Kaldi [33]"

either just one feature map or they have some convolution issues

Encoder - VGG Net Architecture



Encoder - VGG Net Architecture - First six layers

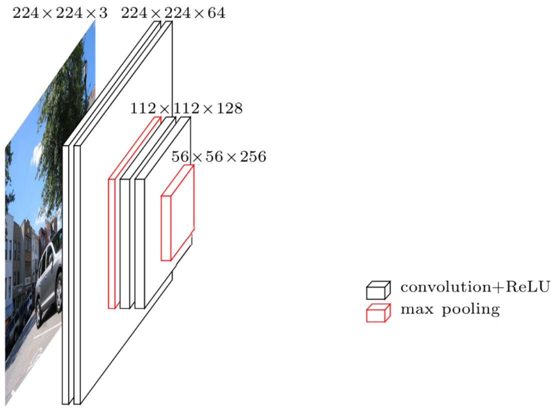


Figure 3: VGG Net - first 6 layers

(actual input dimensions are not mentioned)

Encoder - Bidirectional LSTM layer

320 cells for each direction $\rightarrow$ 640 outputs per time step ($\mathbf{h}_t$)

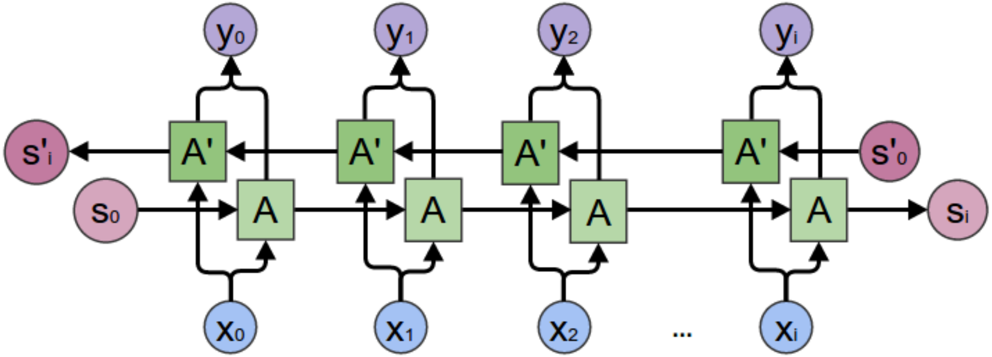


Figure 4: Bidirectional LSTM

http://colah.github.io/posts/2015-09-NN-Types-FP/

Decoder (Attention-based)

Input: $\mathbf{x}_1, \dots, \mathbf{x}_t$

Output: $c_1, \dots, c_l$

1. Encode whole sequence to $\mathbf{h}_1, \dots, \mathbf{h}_t$
2. Calculate soft attention weights a_{lt}, based on
   (a) $a_{(l-1)t}$ (attention on same input for previous output)
   (b) current encoded state $\mathbf{h}_t$
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3. Sum encoded state with soft alignment: $\mathbf{r}_l = \sum_t a_{lt}\mathbf{h}_t$
4. Decoder $=$ Softmax(FC(LSTM($\mathbf{r}_l, \mathbf{q}_{l-1}, c_{l-1}$)))

Problems with this simple model

- Pure temporal attention too flexible, allows nonsensical alignments
  - Intuition: In MT word order can change, in ASR not
- Languages must be implicitly modeled

Additions to the simple model

Problem 1: "Pure temporal attention too flexible"

Add a second, Parallel Decoder with CTC

1. Input (same as before)
2. Encoder (same as before)
3. Decoder

   fully connected softmax layer per time stemp (converts 640 outputs from BLSTM $\rightarrow$ N characters)
4. $\rightarrow$ One output character per input frame, using CTC Loss

CTC Crash Course

Problem: output sequence shorter than input sequence

- First, add blank character "-" to set. e.g. HELLO $\rightarrow \{H, E, L, O, -\}$

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$\rightarrow$ Enforces monotonic alignment

- Efficient computation using Viterbi / forward-backward algorithm
- Loss = negative log of GT probability

https://towardsdatascience.com/intuitively-understanding-connectionist-temporal-classification-3797e43a86c

Problem 2: “Languages must be implicitly modeled”

Add a RNN-LM

- Model distribution of character sequences in languages (ignores input speech)
- Trained seperately

Combine both decoders + RNN-LM

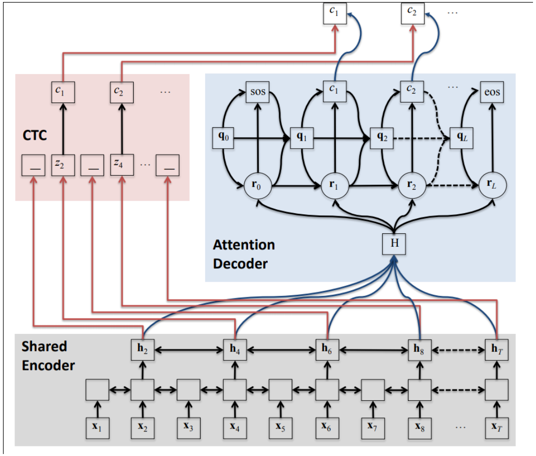


Figure 5: Hybrid CTC/attention-based end-to-end architecture (RNN-LM not shown)

Final loss function

$$\mathcal{L}_{\mathsf{MTL}} = \lambda \log p_{ctc}(C|X) + (1-\lambda) \log p_{att}(C|X) + \gamma \log p_{\mathsf{rnnlm}}(C)$$

$\lambda = 0.5$, $\gamma = 0.1$

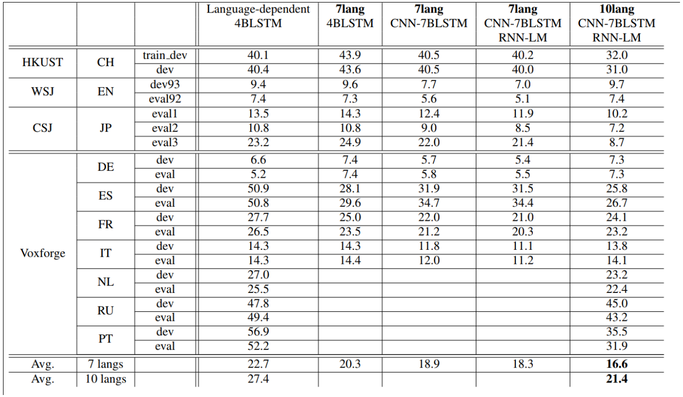
Training

- Inference via beam search on attention output weighted by loss function
- AdaDelta optimization, 15 epochs

Conclusions

- adding a pure language model (RNN-LM) improves performance a bit
- [On single language ASR] “Surprisingly, the method achieved performance comparable to, and in some cases superior to, several state-ofthe-art HMM/DNN ASR systems ... when both multiobjective learning and joint decoding are used.”

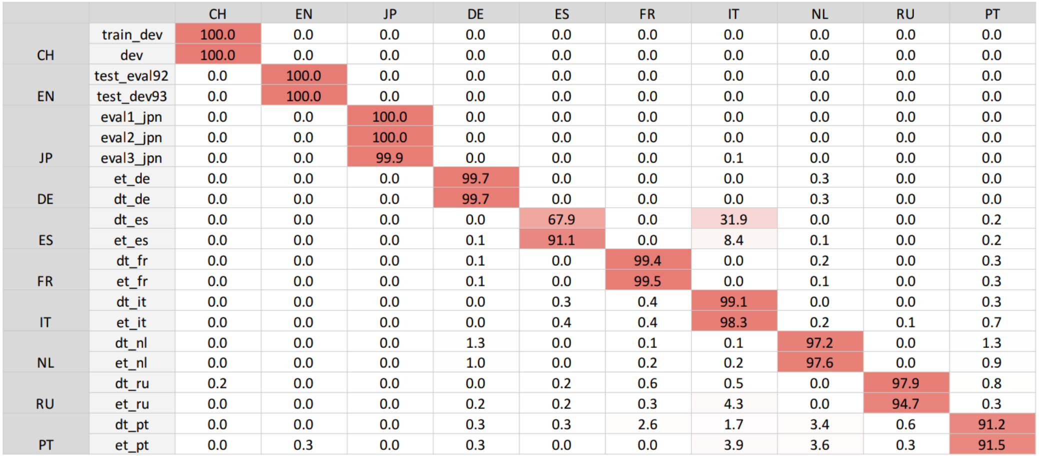
Result Table



			Language-dependent 4BLSTM	**7lang** 4BLSTM	**7lang** CNN-7BLSTM	**7lang** CNN-7BLSTM RNN-LM	**10lang** CNN-7BLSTM RNN-LM
HKUST	CH	train_dev	40.1	43.9	40.5	40.2	32.0
		dev	40.4	43.6	40.5	40.0	31.0
WSJ	EN	dev93	9.4	9.6	7.7	7.0	9.7
		eval92	7.4	7.3	5.6	5.1	7.4
CSJ	JP	eval1	13.5	14.3	12.4	11.9	10.2
		eval2	10.8	10.8	9.0	8.5	7.2
		eval3	23.2	24.9	22.0	21.4	8.7
Voxforge	DE	dev	6.6	7.4	5.7	5.4	7.3
		eval	5.2	7.4	5.8	5.5	7.3
	ES	dev	50.9	28.1	31.9	31.5	25.8
		eval	50.8	29.6	34.7	34.4	26.7
	FR	dev	27.7	25.0	22.0	21.0	24.1
		eval	26.5	23.5	21.2	20.3	23.2
	IT	dev	14.3	14.3	11.8	11.1	13.8
		eval	14.3	14.4	12.0	11.2	14.1
	NL	dev	27.0				23.2
		eval	25.5				22.4
	RU	dev	47.8				45.0
		eval	49.4				43.2
	PT	dev	56.9				35.5
		eval	52.2				31.9
Avg.	7 langs		22.7	20.3	18.9	18.3	**16.6**
Avg.	10 langs		27.4				**21.4**

Figure 6: Character Error Rates (CERs) of language-dependent and language-independent ASR experiments for 7 and 10 multilingual setups.

Language Confusion Matrix



		CH	EN	JP	DE	ES	FR	IT	NL	RU	PT
	train_dev	100.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
CH	dev	100.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	test_eval92	0.0	100.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
EN	test_dev93	0.0	100.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	eval1_jpn	0.0	0.0	100.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	eval2_jpn	0.0	0.0	100.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
JP	eval3_jpn	0.0	0.0	99.9	0.0	0.0	0.0	0.1	0.0	0.0	0.0
	et_de	0.0	0.0	0.0	99.7	0.0	0.0	0.0	0.3	0.0	0.0
DE	dt_de	0.0	0.0	0.0	99.7	0.0	0.0	0.0	0.3	0.0	0.0
	dt_es	0.0	0.0	0.0	0.0	67.9	0.0	31.9	0.0	0.0	0.2
ES	et_es	0.0	0.0	0.0	0.1	91.1	0.0	8.4	0.1	0.0	0.2
	dt_fr	0.0	0.0	0.0	0.1	0.0	99.4	0.0	0.2	0.0	0.3
FR	et_fr	0.0	0.0	0.0	0.1	0.0	99.5	0.0	0.1	0.0	0.3
	dt_it	0.0	0.0	0.0	0.0	0.3	0.4	99.1	0.0	0.0	0.3
IT	et_it	0.0	0.0	0.0	0.0	0.4	0.4	98.3	0.2	0.1	0.7
	dt_nl	0.0	0.0	0.0	1.3	0.0	0.1	0.1	97.2	0.0	1.3
NL	et_nl	0.0	0.0	0.0	1.0	0.0	0.2	0.2	97.6	0.0	0.9
	dt_ru	0.2	0.0	0.0	0.0	0.2	0.6	0.5	0.0	97.9	0.8
RU	et_ru	0.0	0.0	0.0	0.2	0.2	0.3	4.3	0.0	94.7	0.3
	dt_pt	0.0	0.0	0.0	0.3	0.3	2.6	1.7	3.4	0.6	91.2
PT	et_pt	0.0	0.3	0.0	0.3	0.0	0.0	3.9	3.6	0.3	91.5

Figure 7: Language identification (LID) accuracies/error rates (%). The diagonal elements correspond to the LID accuracies while the offdiagonal elements correspond to the LID error rates

Potential problems / future work?

- Nothing ensures language does not switch mid sentence $\rightarrow$ Apparently not an issue
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  - Bidirectional LSTM in encoder
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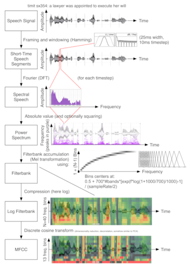
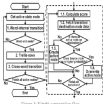
- Unbalanced language sets (500h CH, 2.9h PR)
- Same latin characters are used for multiple languages, while others (RU, CH, JP) get their own character set
  - Try transliterating them to Latin?

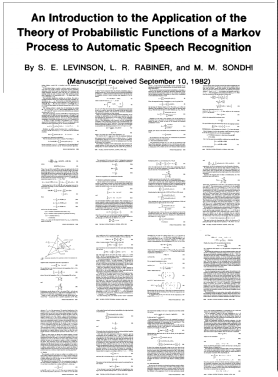
Thank you for your attention

WHO WOULD WIN?

decades of research on Feature extraction,
Dynamic time warping, HMMs, Language modeling


timit sx354: a lawyer was appointed to execute her will
Speech Signal
Amplitude
Time
Framing and windowing (Hamming)
(25ms width, 10ms timestep)
Short-Time Speech Segments
Fourier (DFT)
(for each timestep)
Spectral Speech
Frequency
Absolute value (and optionally squaring)
Power Spectrum
Frequency (peaks in purple)
Filterbank accumulation (Mel transformation) using:
1 + (N-1) Bins
Filterbank
Bins centers at: 0.5 + 700*#bands*[exp(f*log(1+1000/700)/1000)-1] / (sampleRate/2)
Compression (here log)
Log Filterbank
N=40 freq. bins
Discrete cosine transform
MFCC
13 freq. bins


Start
Get active state node
1. Word-internal transition
Word-end node?
2. Trellis-save
3. Cross-word transition
Finish all active nodes?
End
1.1. Calculate score
1.2. Fetch transition destination node data
Is there active node on destination?
1.3. Create active node
Does source node have higher probability?
1.4. Overwrite active node
Finish all transition?
Yes
No
Figure 1: Viterbi computation flow



An Introduction to the Application of the Theory of Probabilistic Functions of a Markov Process to Automatic Speech Recognition

By S. E. LEVINSON, L. R. RABINER, and M. M. SONDHI

(Manuscript received September 10, 1982)

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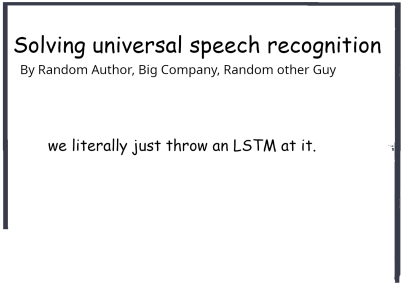

Solving universal speech recognition

By Random Author, Big Company, Random other Guy

we literally just throw an LSTM at it.