Towards End-to-End Speech Recognition

Rohit Prabhavalkar and Tara N. Sainath
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Acknowledgements

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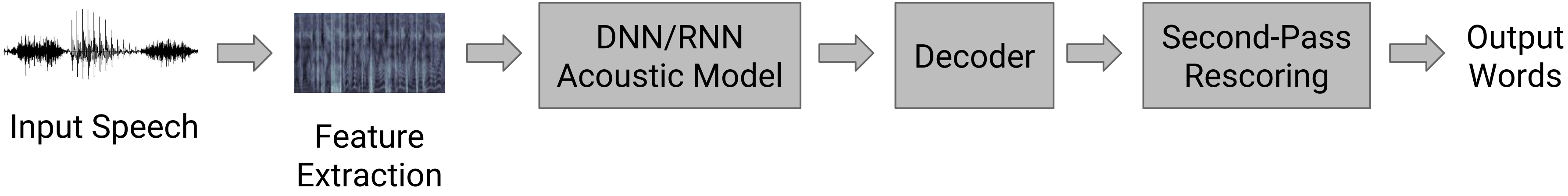
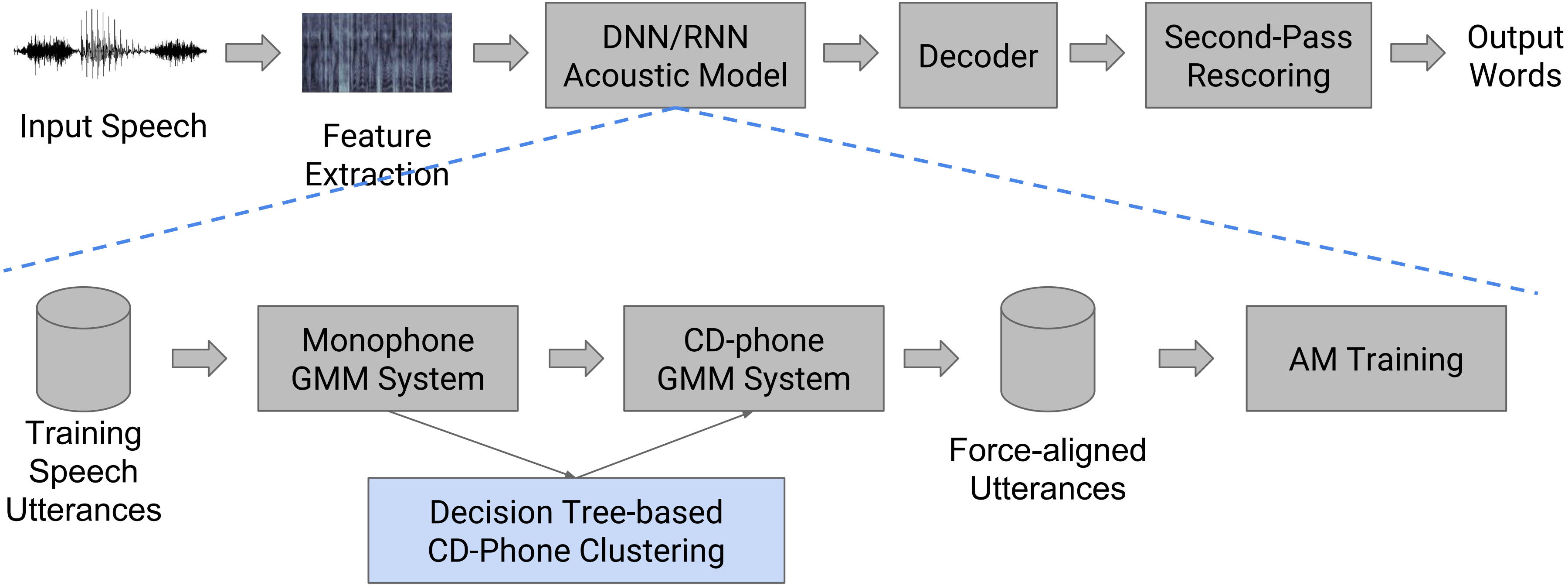
What is End-to-End ASR?

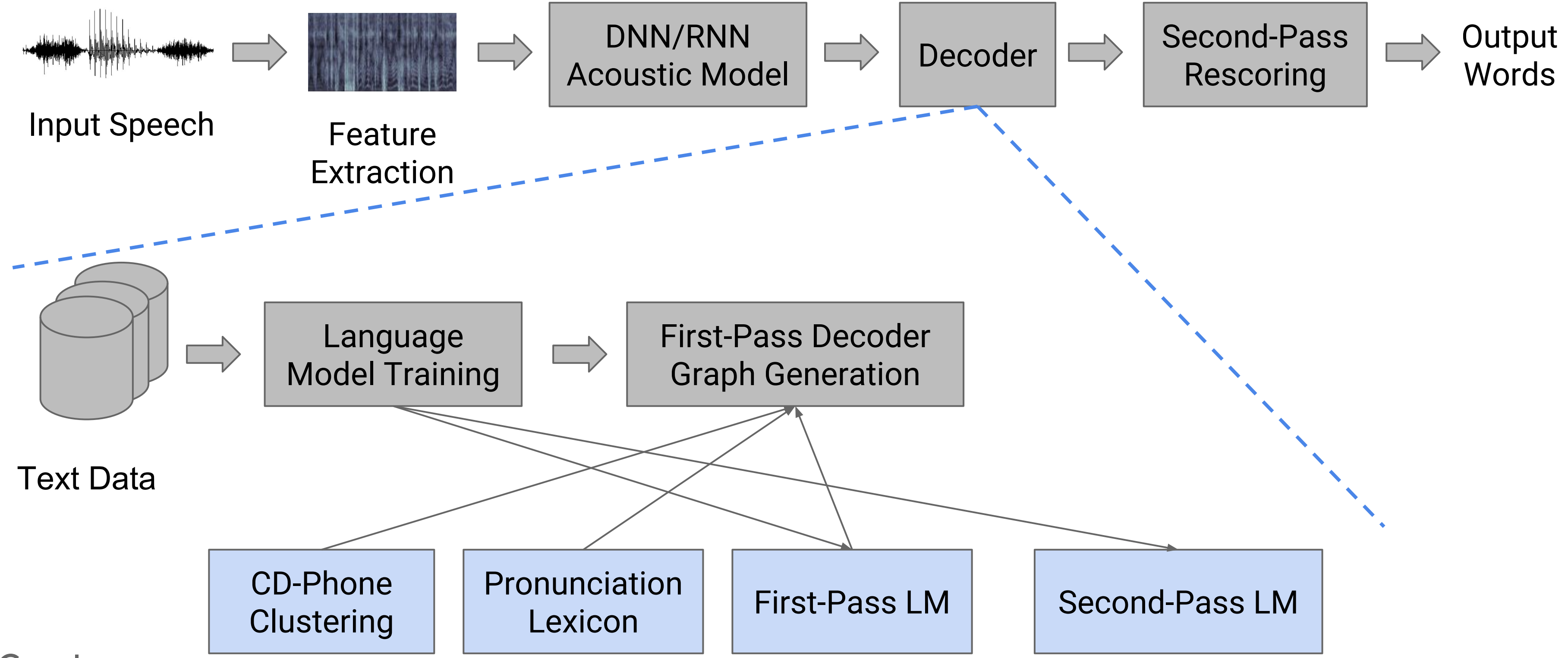
Conventional ASR Pipeline



Conventional ASR Pipeline: AM Training



Conventional ASR Pipeline: LM Training



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Conventional ASR Pipeline

- Most ASR systems involve separately trained acoustic, pronunciation and language model components which are trained separately
  - Discriminative Sequence Training of AMs does couple these components
- Curating pronunciation lexicon, defining phoneme sets for the particular language requires expert knowledge, and is time-consuming

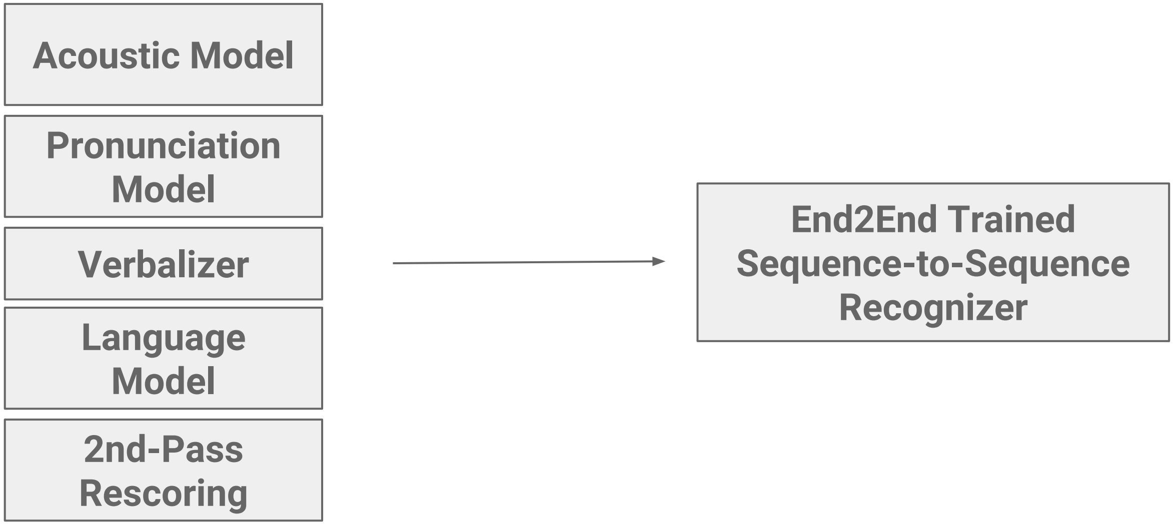
What is “End-to-End” ASR?

“A system which directly maps a sequence of input acoustic features into a sequence of graphemes or words.”

“A system which is trained to optimize criteria that are related to the final evaluation metric that we are interested in (typically, word error rate).”

Motivation: End-to-End ASR

Typical Speech System



A single end-to-end trained sequence-to-sequence model, which directly outputs words or graphemes, could greatly simplify the speech recognition pipeline

Historical Development of End-to-End ASR

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Connectionist Temporal Classification (CTC)

- CTC was proposed by [Graves et al., 2006] as a way to train an acoustic model without requiring frame-level alignments
- Early work, used CTC with phoneme output targets - not "end-to-end"
- CD-phoneme based CTC models achieve state-of-the art performance for conventional, word-level lagged behind ASR [Sak et al., 2015]

Connectionist Temporal Classification: Labelling Unsegmented Sequence Data with Recurrent Neural Networks

Alex Graves[1] ALEX@IDSIA.CH
Santiago Fernández[1] SANTIAGO@IDSIA.CH
Faustino Gomez[1] TINO@IDSIA.CH
Jürgen Schmidhuber[1,2] JUERGEN@IDSIA.CH
[1] Istituto Dalle Molle di Studi sull'Intelligenza Artificiale (IDSIA), Galleria 2, 6928 Manno-Lugano, Switzerland
[2] Technische Universität München (TUM), Boltzmannstr. 3, 85748 Garching, Munich, Germany

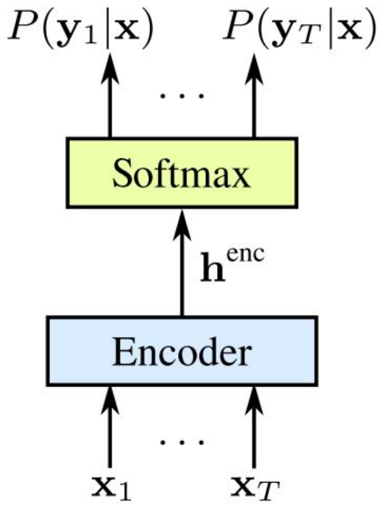
Abstract

Many real-world sequence learning tasks require the prediction of sequences of labels from noisy, unsegmented input data. In

belling. While these approaches have proved successful for many problems, they have several drawbacks: (1) they usually require a significant amount of task specific knowledge, e.g. to design the state models for HMMs, or choose the input features for CRFs; (2)

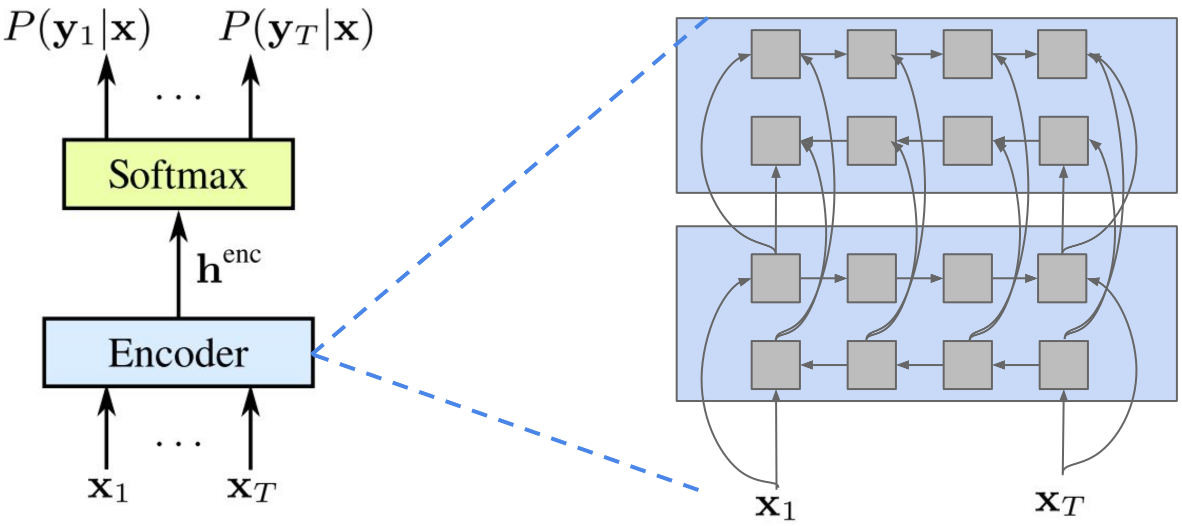
[Graves et al., 2006] ICML

Connectionist Temporal Classification (CTC)



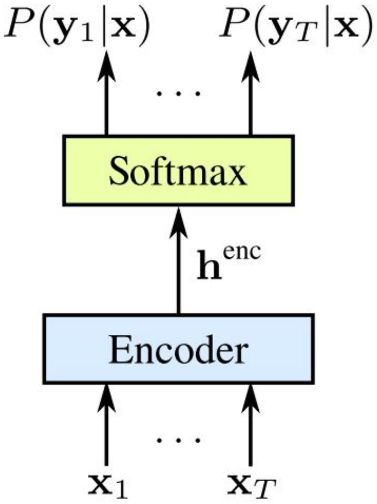
CTC allows for training an acoustic model without the need for frame-level alignments between the acoustics and the transcripts

Connectionist Temporal Classification (CTC)



Encoder: Multiple layers of Uni- or Bi-directional RNNs (often LSTMs)

Connectionist Temporal Classification (CTC)

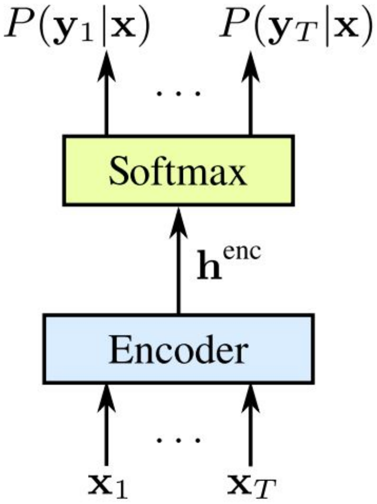



```
B B c B B a a B B t
B c c B a B B B B t
        ...
B c B B a B B t t B
```

$$P(\mathbf{y}|\mathbf{x}) = \sum_{\hat{\mathbf{y}} \in \mathcal{B}(\mathbf{y},\mathbf{x})} \prod_{t=1}^{T} P(\hat{y}_t|\mathbf{x})$$

CTC introduces a special symbol - blank (denoted by B) - and maximizes the total probability of the label sequence by marginalizing over all possible alignments

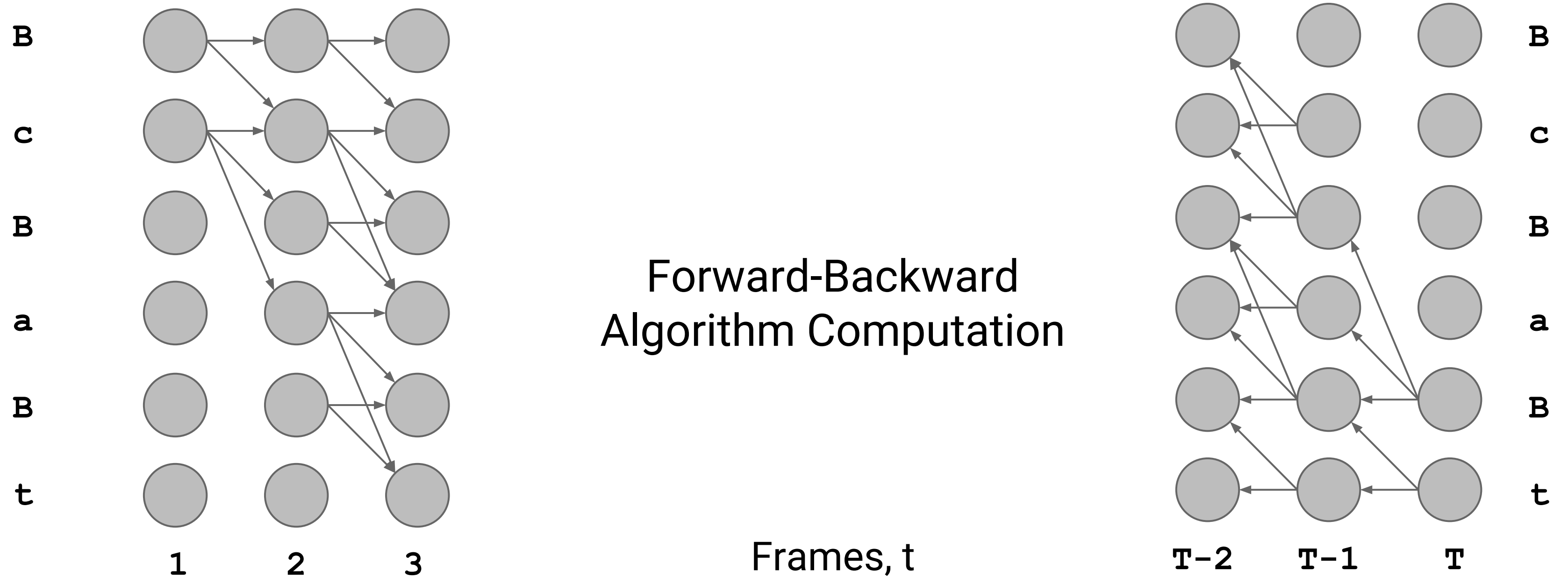
Connectionist Temporal Classification (CTC)



B B **c** B B **a** **a** B B **t**
B **c** **c** B **a** B B B B **t**
...
B **c** B B **a** B B **t** **t** B

In a conventional hybrid system, this would correspond to defining the HMMs corresponding to each unit to consist of a shared initial state (blank), followed by a separate state(s) for the actual unit

Connectionist Temporal Classification (CTC)



- Computing the gradients of the loss requires the computation of the alpha-beta variables using the forward-backward algorithm [Rabiner, 1989]

CTC-Based End-to-End ASR

- Graves and Jaitly proposed a system with character-based CTC which directly output word sequences given input speech
- Using an external LM was important for getting good performance. Results reported by rescoring a baseline system.
- Also proposed minimizing expected transcription error [WSJ: 8.7% → 8.2%]

Towards End-to-End Speech Recognition with Recurrent Neural Networks

Alex Graves GRAVES@CS.TORONTO.EDU
Google DeepMind, London, United Kingdom

Navdeep Jaitly NDJAITLY@CS.TORONTO.EDU
Department of Computer Science, University of Toronto, Canada

Abstract

This paper presents a speech recognition system that directly transcribes audio data with text, without requiring an intermediate phonetic representation. The system is based on a combination

fits of holistic optimisation tend to outweigh those of prior knowledge.

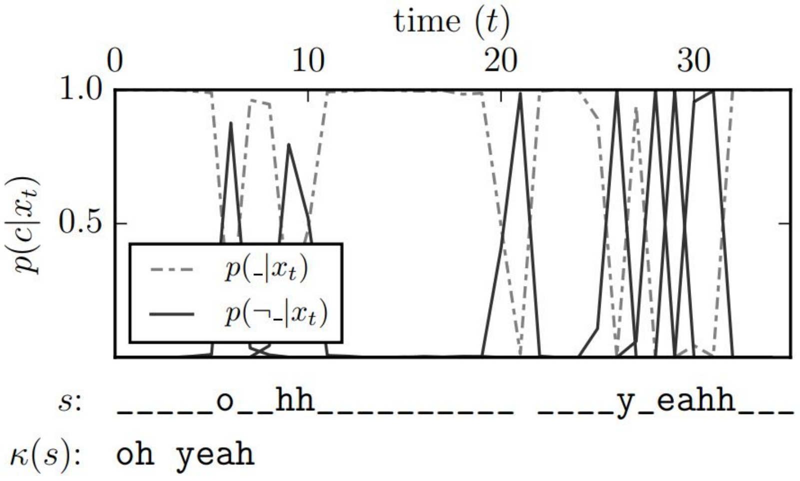
While automatic speech recognition has greatly benefited from the introduction of neural networks (Bourlard & Morgan, 1993; Hinton et al., 2012), the networks are at present

[Graves and Jaitly, 2014] ICML

CTC-Based ASR: Refinements since [Graves & Jaitly, 2014]

- LM incorporated into first-pass decoding; easy integration with WFSTs
  - [Hannun et al., 2014] [Maas et al., 2015]: Direct first-pass decoding with an LM as opposed to rescoring as in [Graves & Jaitly, 2014]
  - [Miao et al., 2015]: EESEN framework for decoding with WFSTs, open source toolkit
- Large-scale GPU training; data augmentation; multiple languages
  - [Hannun et al., 2014; DeepSpeech] [Amodei et al., 2015; DeepSpeech2]: Large scale GPU training; Data Augmentation; Mandarin and English
- Using longer span units: words instead of characters
  - [Soltau et al., 2017]: Word-level CTC targets, trained on 125,000 hours of speech. Performance close to or better than a conventional system, even without using an LM!
  - [Audhkhasi et al., 2017]: Direct Acoustics-to-Word Models on Switchboard
- And many others ...

CTC-Based End-to-End ASR



CTC produces “spiky” and sparse activations - can sometimes directly read off the final transcription from the activations even without an LM

Reproduced from [Maas et al., 2015] NAACL

CTC-Based End-to-End ASR

#	Method	Transcription
(1)	Truth	yeah i went into the i do not know what you think of *fidelity* but
	HMM-GMM	yeah when the i don't know what you think of fidel it even them
	CTC+CLM	yeah i went to i don't know what you think of fidelity but um
(2)	Truth	no no speaking of weather do you carry a altimeter slash *barometer*
	HMM-GMM	no i'm not all being the weather do you uh carry a uh helped emitters last brahms her
	CTC+CLM	no no beating of whether do you uh carry a uh a time or less barometer
(3)	Truth	i would ima- well yeah it is i know you are able to stay home with them
	HMM-GMM	i would amount well yeah it is i know um you're able to stay home with them
	CTC+CLM	i would ima- well yeah it is i know uh you're able to stay home with them

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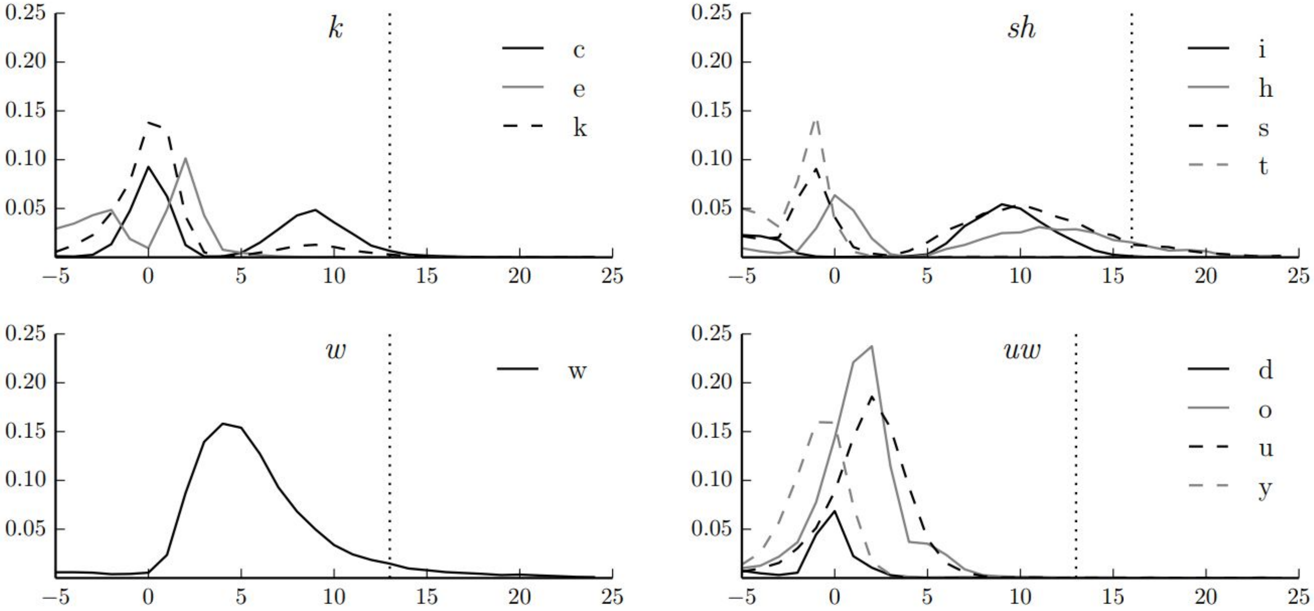
CTC-Based End-to-End ASR



Reproduced from [Maas et al., 2015] NAACL

Google

Shortcomings of CTC

- For efficiency, CTC makes an important independence assumption - network outputs at different frames are conditionally independent
- Obtaining good performance from CTC models requires the use of an external language model - direct greedy decoding does not perform very well

Recurrent Neural Network Transducer (RNN-T)

- Proposed by Graves et al., RNN-T augments a CTC-based model with a recurrent LM component
- Both components are trained jointly on the available acoustic data
- As with CTC, the method does not require aligned training data.

SPEECH RECOGNITION WITH DEEP RECURRENT NEURAL NETWORKS

Alex Graves, Abdel-rahman Mohamed and Geoffrey Hinton

Department of Computer Science, University of Toronto

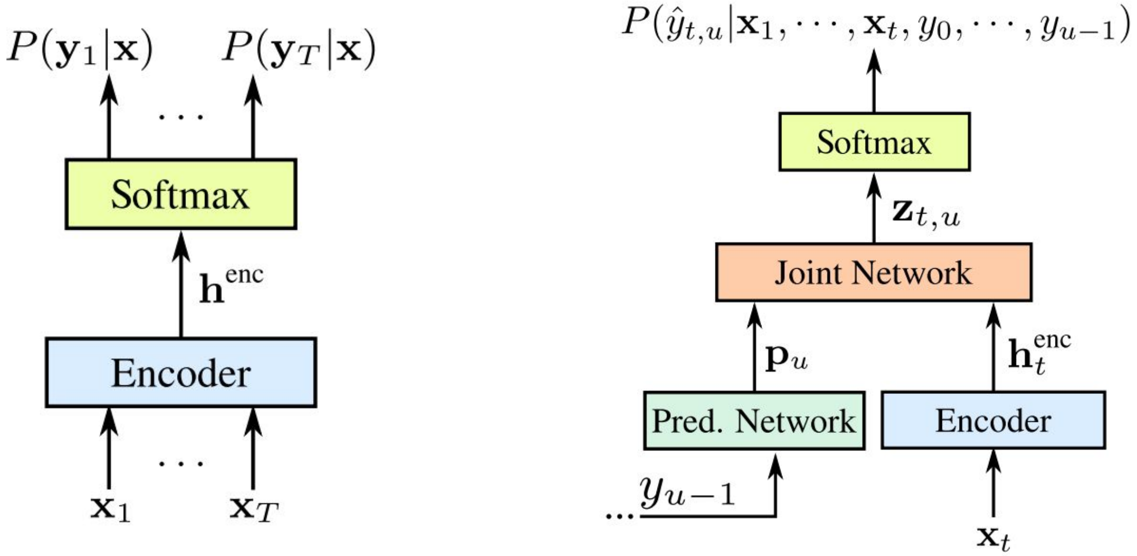
ABSTRACT

Recurrent neural networks (RNNs) are a powerful model for sequential data. End-to-end training methods such as Connectionist Temporal Classification make it possible to train RNNs for sequence labelling problems where the input-output alignment is unknown. The combination of these methods with

RNNs are inherently deep in time, since their hidden state is a function of all previous hidden states. The question that inspired this paper was whether RNNs could also benefit from depth in space; that is from stacking multiple recurrent hidden layers on top of each other, just as feedforward layers are stacked in conventional deep networks. To answer this ques-

[Graves et al., 2013] ICASSP;
[Graves, 2012] ICML Representation Learning Workshop

Recurrent Neural Network Transducer (RNN-T)



RNN-T [Graves, 2012] augments CTC encoder with a recurrent neural network LM

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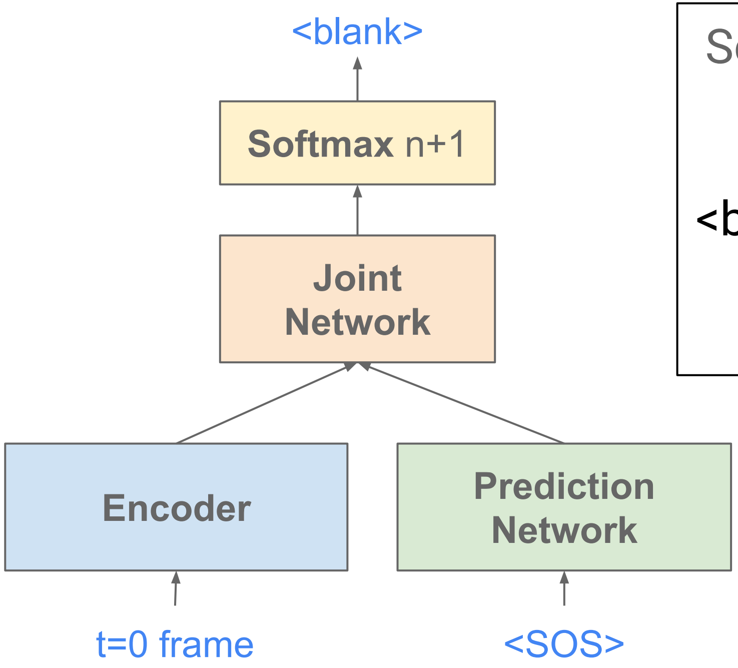
Recurrent Neural Network Transducer (RNN-T)

Output:



Softmax over n + 1 labels, includes a blank like CTC.

<blank> → advance in Encoder, retain prediction network state

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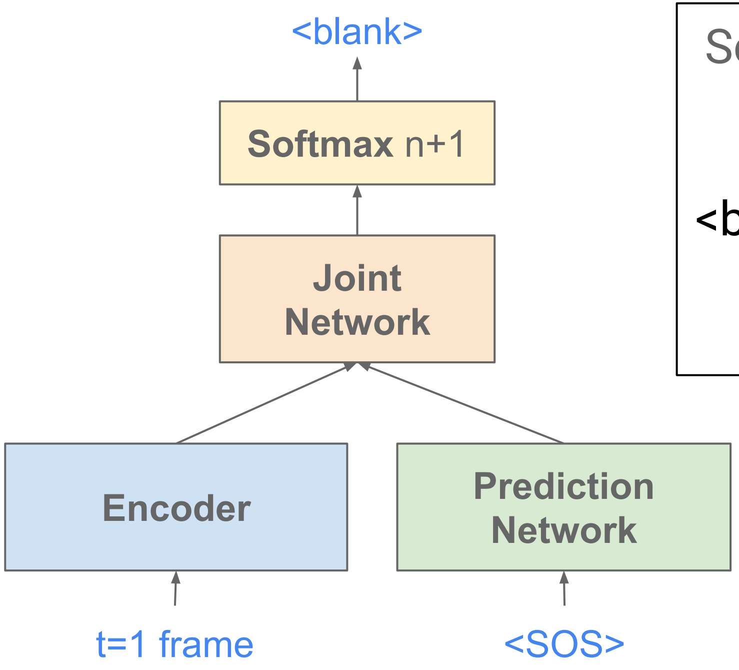
Recurrent Neural Network Transducer (RNN-T)

Output:



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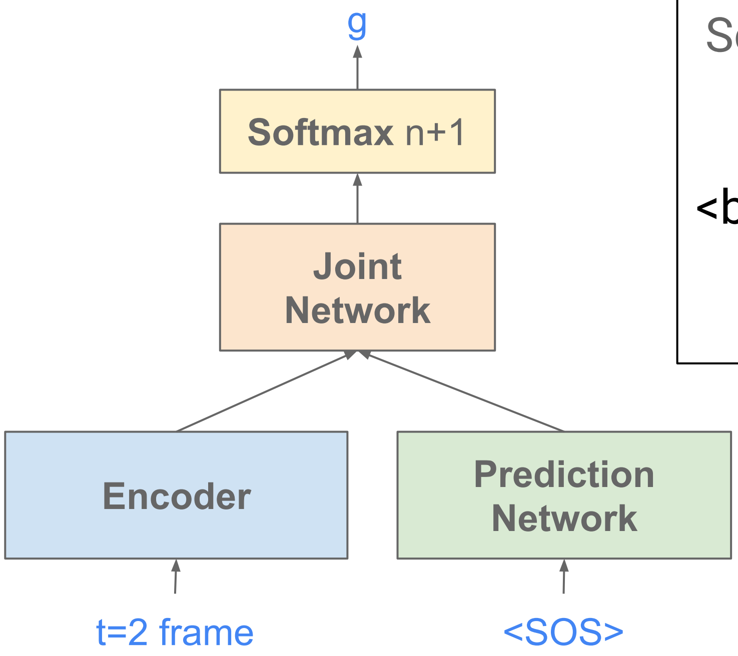
Recurrent Neural Network Transducer (RNN-T)

Output: g



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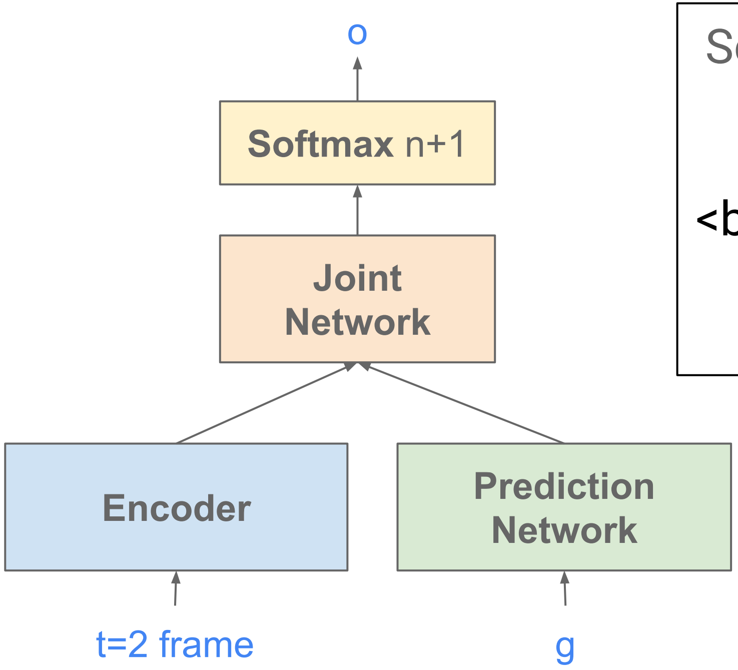
Recurrent Neural Network Transducer (RNN-T)

Output: go



Softmax over n + 1 labels, includes a blank like CTC.

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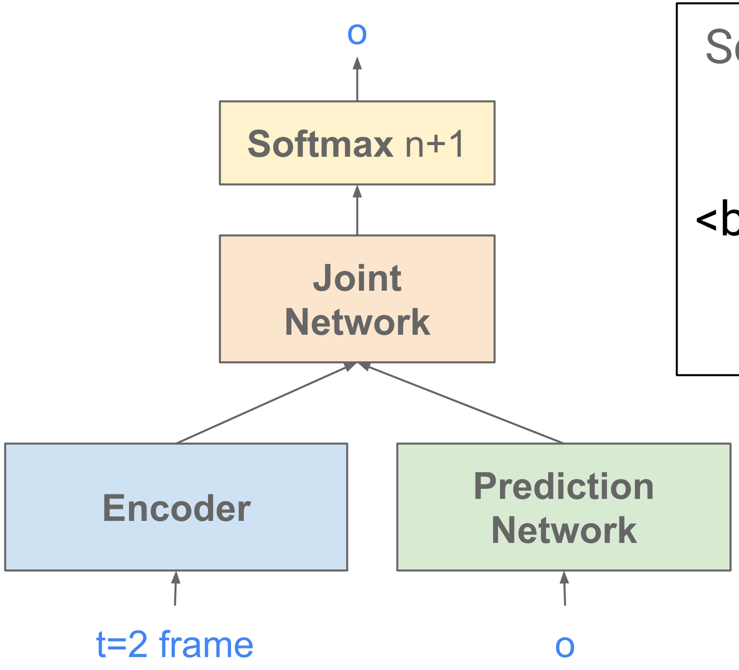
Recurrent Neural Network Transducer (RNN-T)

Output: goo



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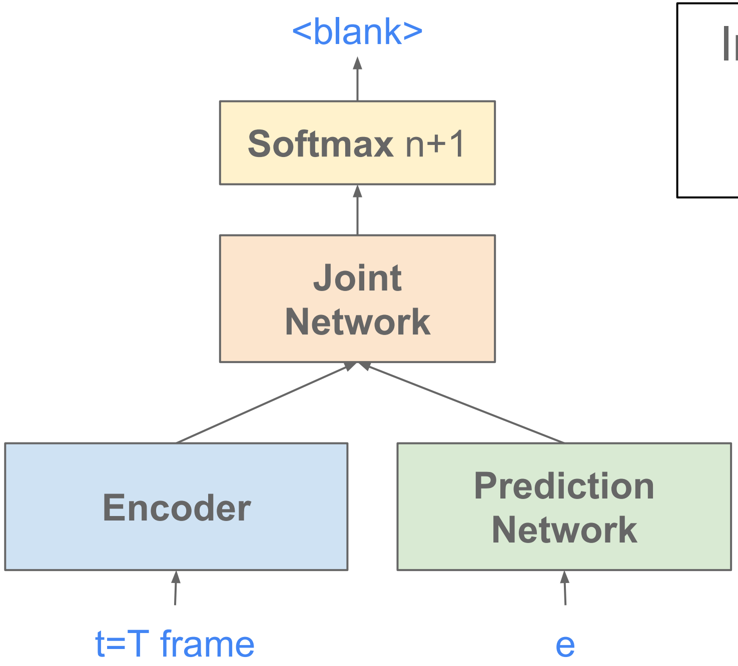
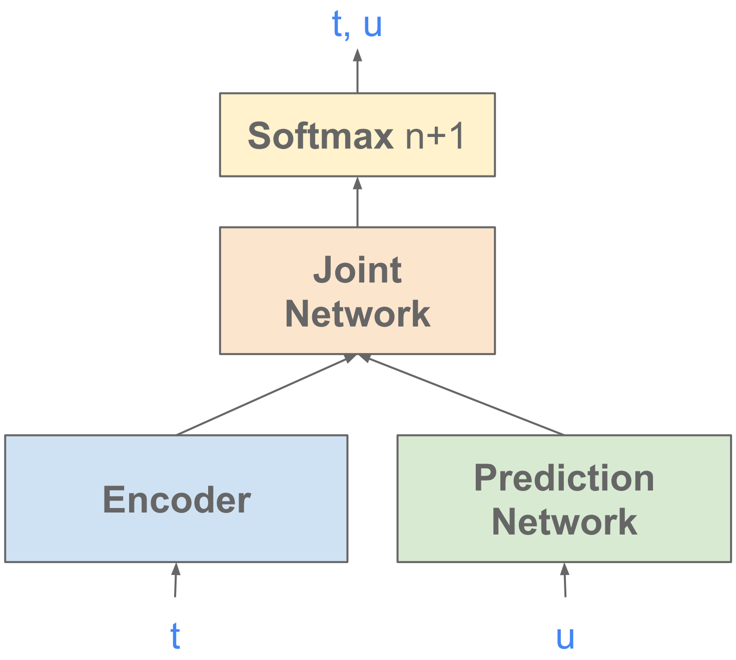


Output: google

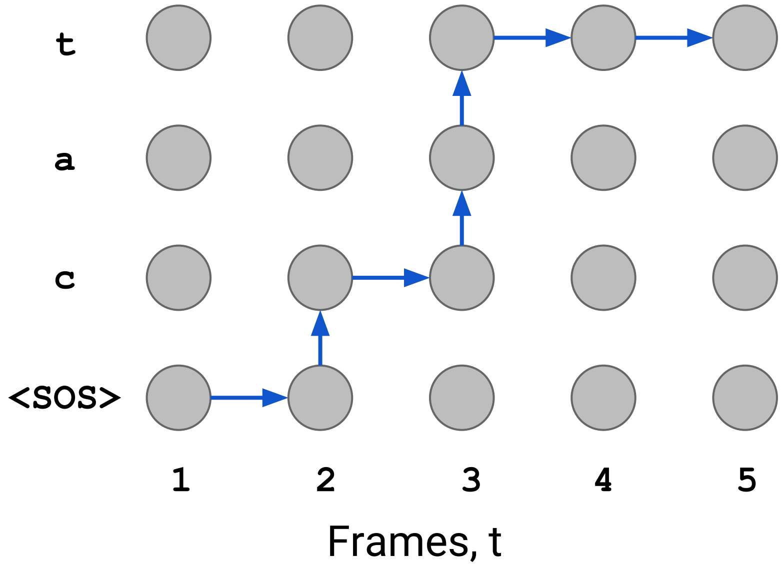
Inference terminates when all input frames have been consumed

Google

Recurrent Neural Network Transducer (RNN-T)



During training feed the true label sequence to the LM.
Given a target sequence of length U and T acoustic frames we generate UxT softmax



Recurrent Neural Network Transducer (RNN-T)

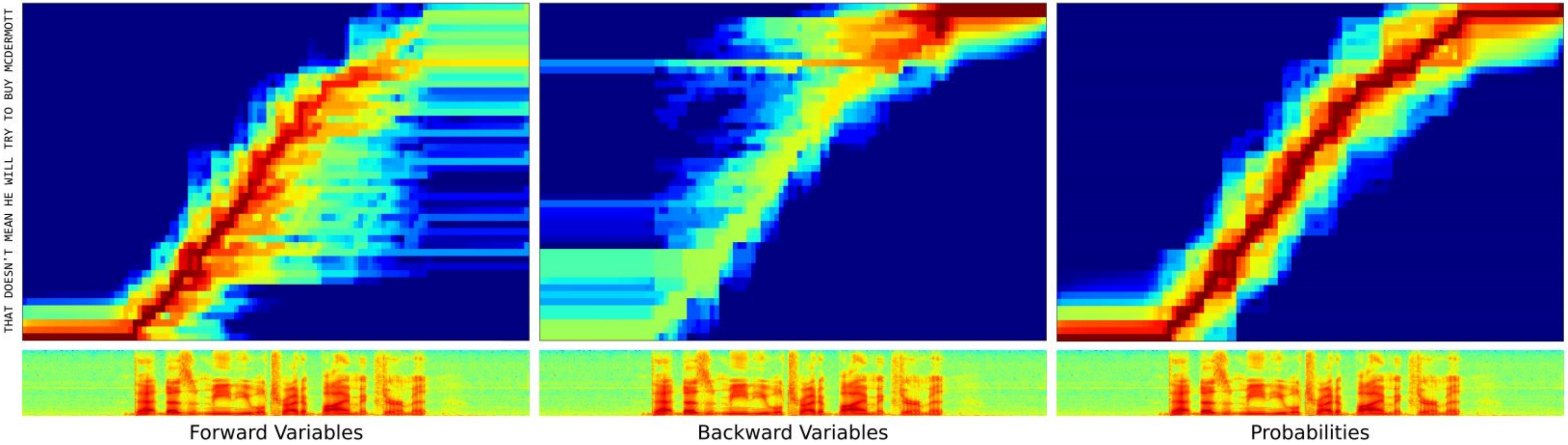


Figure 2. **Forward-backward variables during a speech recognition task.** The image at the bottom is the input sequence: a spectrogram of an utterance. The three heat maps above that show the logarithms of the forward variables (top) backward variables (middle) and their product (bottom) across the output lattice. The text to the left is the target sequence.

Reproduced from [Graves, 2012] ICML Representation Learning Workshop

Recurrent Neural Network Transducer (RNN-T)

Table 1. TIMIT Phoneme Recognition Results. 'Epochs' is the number of passes through the training set before convergence. 'PER' is the phoneme error rate on the core test set.

NETWORK	WEIGHTS	EPOCHS	PER
CTC-3L-500H-TANH	3.7M	107	37.6%
CTC-1L-250H	0.8M	82	23.9%
CTC-1L-622H	3.8M	87	23.0%
CTC-2L-250H	2.3M	55	21.0%
CTC-3L-421H-UNI	3.8M	115	19.6%
CTC-3L-250H	3.8M	124	18.6%
CTC-5L-250H	6.8M	150	18.4%
TRANS-3L-250H	4.3M	112	18.3%
PRETRANS-3L-250H	**4.3M**	**144**	**17.7%**

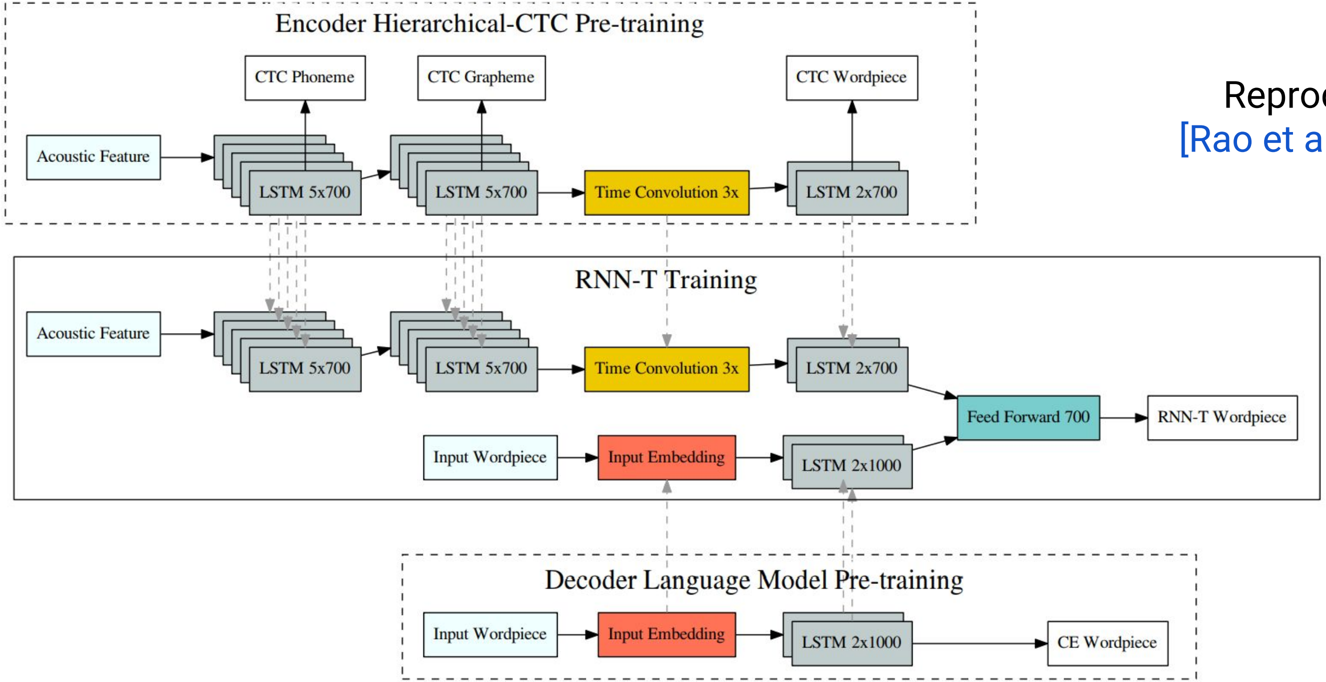
[Graves et al., 2013] showed promising results on TIMIT phoneme recognition, but the work did not seem to get as much traction in the field as CTC.

Reproduced from [Graves, 2013] ICASSP

Recurrent Neural Network Transducer (RNN-T)

- Intuitively, the prediction network corresponds to the "language model" component and the encoder corresponds to the "acoustic model" component
    - Both components can be initialized from a separately trained CTC-AM and a RNN-LM (which can be trained on text only data)
    - Initialization provides some gains [Rao et al., 2017] but is not critical to get good performance
- Generally speaking, RNN-T always seems to perform better than CTC alone in our experiments (even when decoded with a separate LM)
    - More on this in a bit when we compare various approaches on a voice search task.

RNN-T: Case Study on ~18,000 hour Google Data



Reproduced from
[Rao et al., 2017] ASRU

RNN-T components can be initialized separately from (hierarchical) CTC-trained AM, and recurrent LM. Initialization generally improves performance.

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RNN-T: Case Study on ~18,000 hour Google Data

- If graphemes are used as output units, then the model has limited language modeling context: e.g. errors: “the tortoise and the hair”
- Using words as output targets would allow modeling additional context, but would introduce OOVs
- Intermediate: Use “word pieces” [Schuster & Nakajima, 2012]
    - Iteratively learn a vocabulary of units from text data.
    - Start with single graphemes, and train an LM from the data.
    - Iteratively combine units in a greedy manner which improve training perplexity
    - Continue to combine units until reaching a predefined number of units or perplexity improvements are below a threshold
    - E.g., “tortoise and the hare” → _tor to ise _and _the _hare

RNN-T: Case Study on ~18,000 hour Google Data

	Layers		Pre-trained		Training Data Used				WER(%)	
Units	Encoder	Decoder	Encoder	Decoder	Acoustic	Pronunciation	Text	Params	VS	IME
RNN-T										
Graphemes	5x700	2x700	no	no	yes	no	no	21M	13.9	8.4
Graphemes	5x700	2x700	yes	no	yes	no	no	21M	13.2	8.0
Graphemes	8x700	2x700	yes	no	yes	no	no	33M	12.0	6.9
Graphemes	8x700	2x700	yes	no	yes	yes	no	33M	11.4	6.8
Graphemes	8x700	2x700	yes	yes	yes	yes	yes	33M	10.8	6.4
Wordpieces-1k	12x700	2x700	yes	yes	yes	yes	yes	55M	9.9	6.0
Wordpieces-10k	12x700	2x700	yes	yes	yes	yes	yes	66M	9.1	5.3
Wordpieces-30k	12x700	2x1000	yes	yes	yes	yes	yes	96M	8.5	5.2
Baseline										
-	-	-	-	-	yes	yes	yes	120.2M	8.3	5.4

Initializing the “encoder” (i.e., acoustic model) helps improve performance by ~5%.

RNN-T: Case Study on ~18,000 hour Google Data

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Baseline										
-	-	-	-	-	yes	yes	yes	120.2M	8.3	5.4

Initializing the “prediction network” (i.e., prediction network) helps improve performance by ~5%.

RNN-T: Case Study on ~18,000 hour Google Data

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Baseline										
-	-	-	-	-	yes	yes	yes	120.2M	8.3	5.4

The RNN-T model with ~96M parameters can match the performance of a conventional sequence-trained CD-phone based CTC model with a large first pass LM

Attention-based Encoder-Decoder Models

- Attention-based Encoder-Decoder Models emerged first in the context of neural machine translation.
- Were first applied to ASR by [Chan et al., 2015] [Chorowski et al., 2015]

Listen, Attend and Spell

William Chan
Carnegie Mellon University
williamchan@cmu.edu

Navdeep Jaitly, Quoc V. Le, Oriol Vinyals
Google Brain
{ndjaitly,qvl,vinyals}@google.com

[Chan et al., 2015]

Attention-Based Models for Speech Recognition

Jan Chorowski
University of Wrocław, Poland
jan.chorowski@ii.uni.wroc.pl

Dzmitry Bahdanau
Jacobs University Bremen, Germany

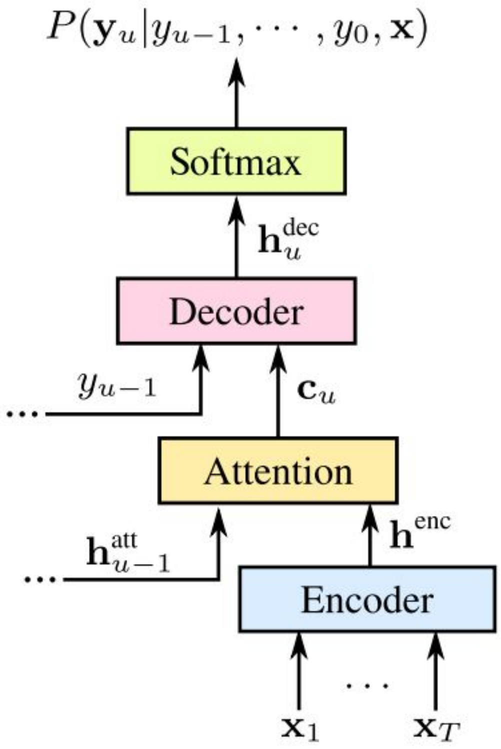
Dmitriy Serdyuk
Université de Montréal

Kyunghyun Cho
Université de Montréal

Yoshua Bengio
Université de Montréal
CIFAR Senior Fellow

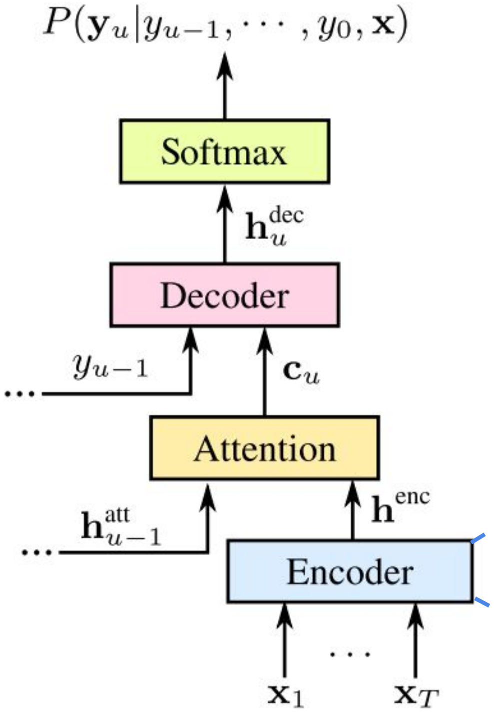
[Chorowski et al., 2015]

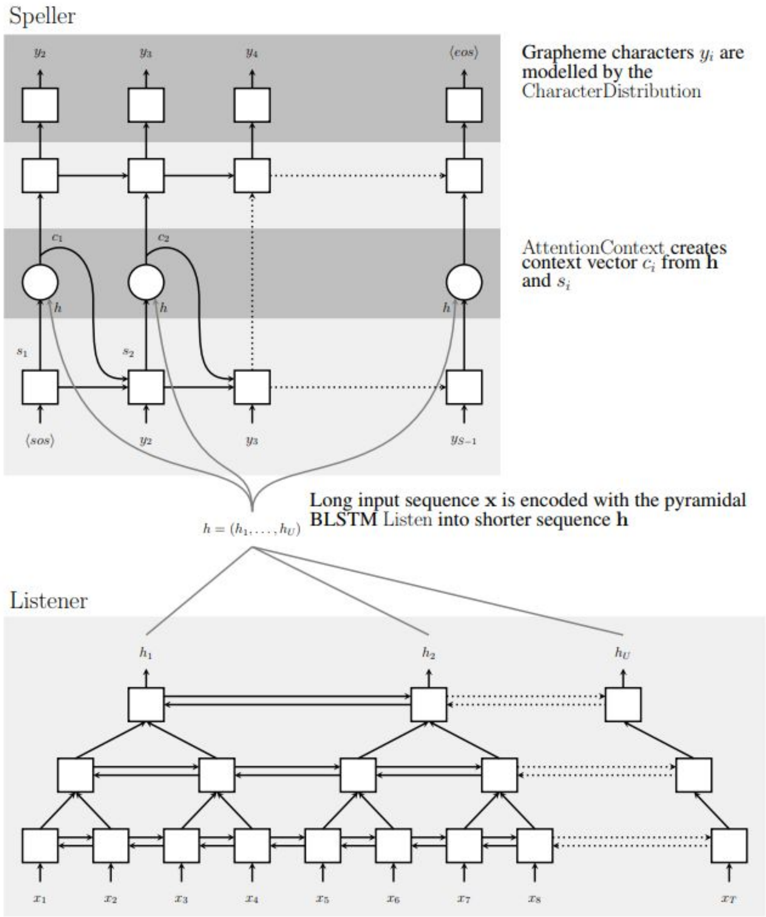
Attention-based Encoder-Decoder Models



- Encoder (analogous to AM):
  - Transforms input speech into higher-level representation
- Attention (alignment model):
  - Identifies encoded frames that are relevant to producing current output
- Decoder (analogous to PM, LM):
  - Operates autoregressively by predicting each output token as a function of the previous predictions

Attention-Based Models





Reproduced from [Chan et al., 2015]

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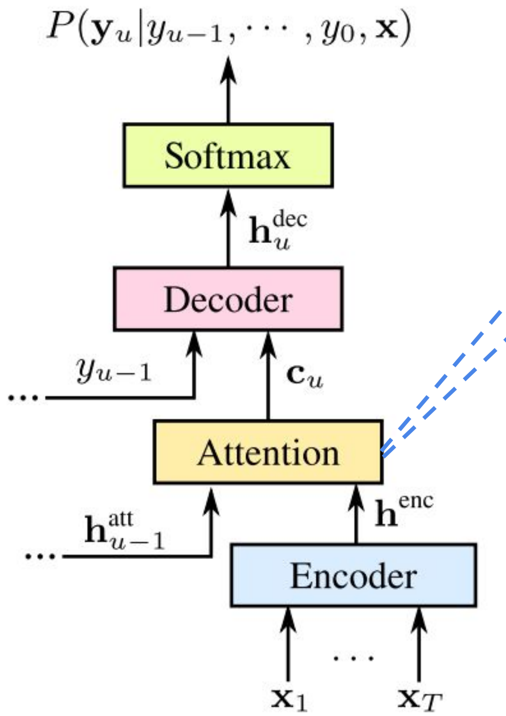
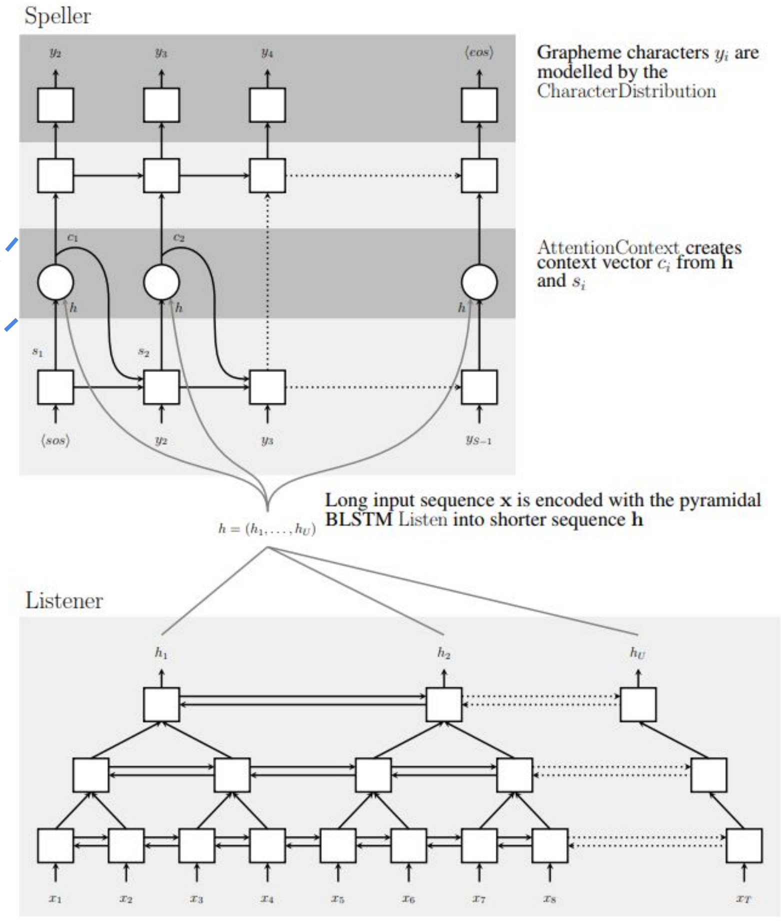
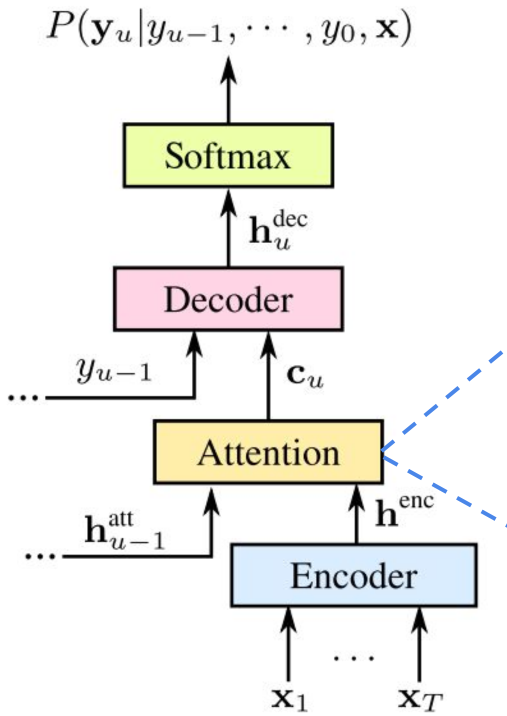
Attention-Based Models





Reproduced from [Chan et al., 2015]

Attention-Based Models



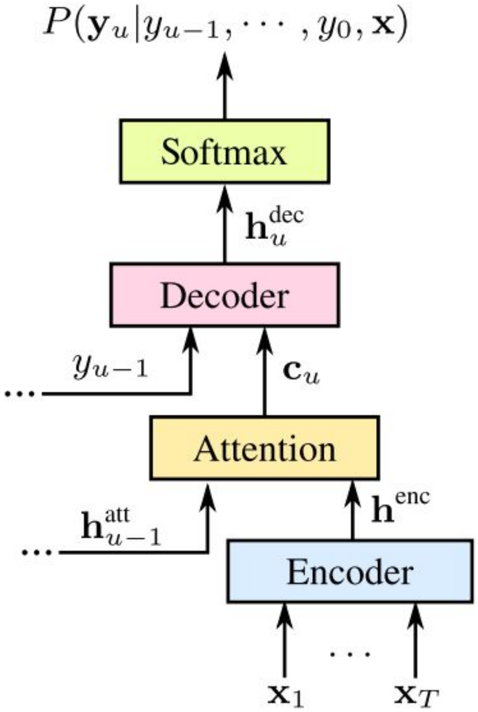
Attention module computes a similarity score between the decoder and each frame of the encoder

$$e_{u,t} = \text{score}(\mathbf{h}_{u-1}^{\text{att}}, \mathbf{h}_t^{\text{enc}})$$

$$\alpha_{u,t} = \frac{\exp(e_{u,t})}{\sum_{t'=1}^{T} \exp(e_{u,t'})}$$

$$\mathbf{c}_u = \sum_{t=1}^{T} \alpha_{u,t} h_t^{\text{enc}}$$

Attention-Based Models



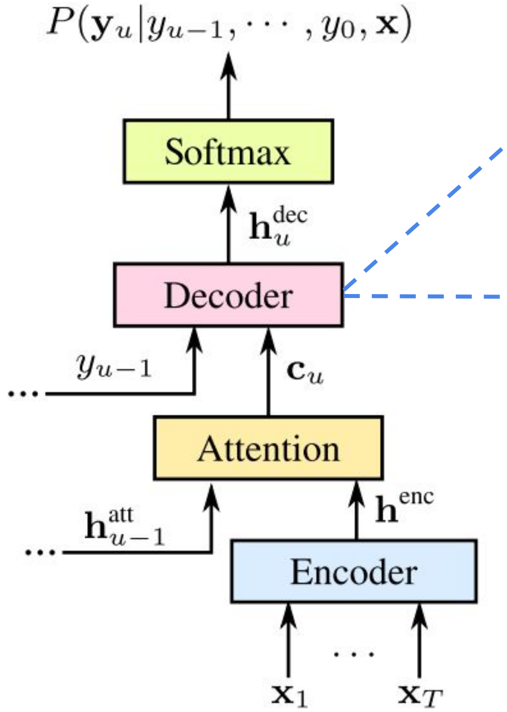
Dot-Product Attention [Chan et al., 2015]

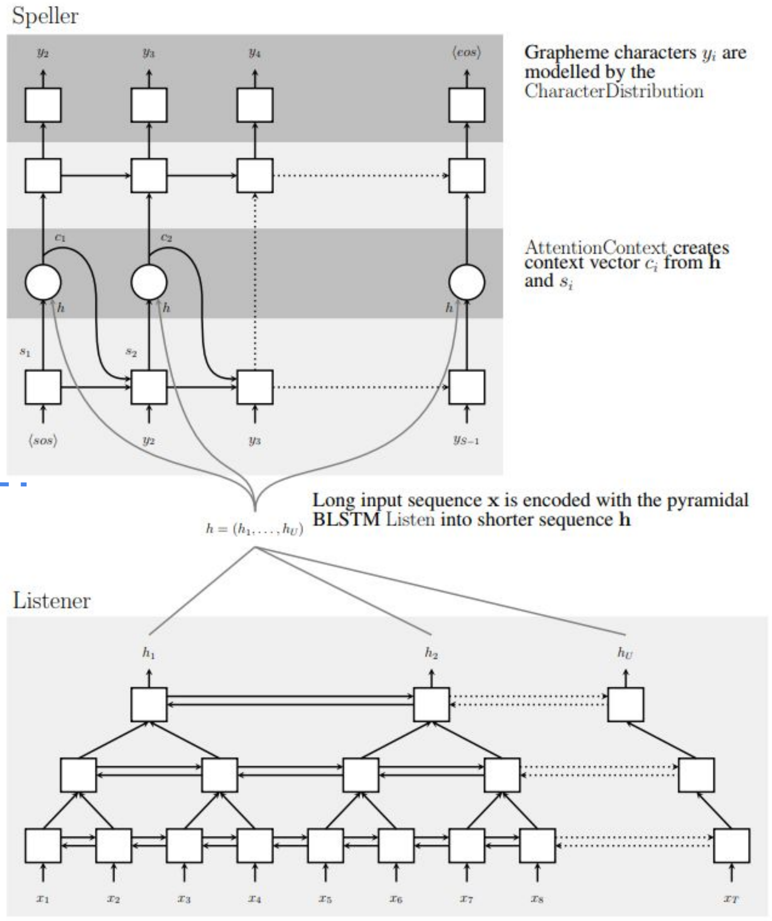
$$e_{u,t} = \left\langle \phi(W\mathbf{h}_{u-1}^{\text{att}}),\ \psi(V\mathbf{h}_t^{\text{enc}}) \right\rangle$$

Additive Attention [Chorowski et al., 2015]

$$e_{u,t} = w^T \tanh(W\mathbf{h}_{u-1}^{\text{att}} + V\mathbf{h}_t^{\text{enc}} + b)$$

Attention-Based Models



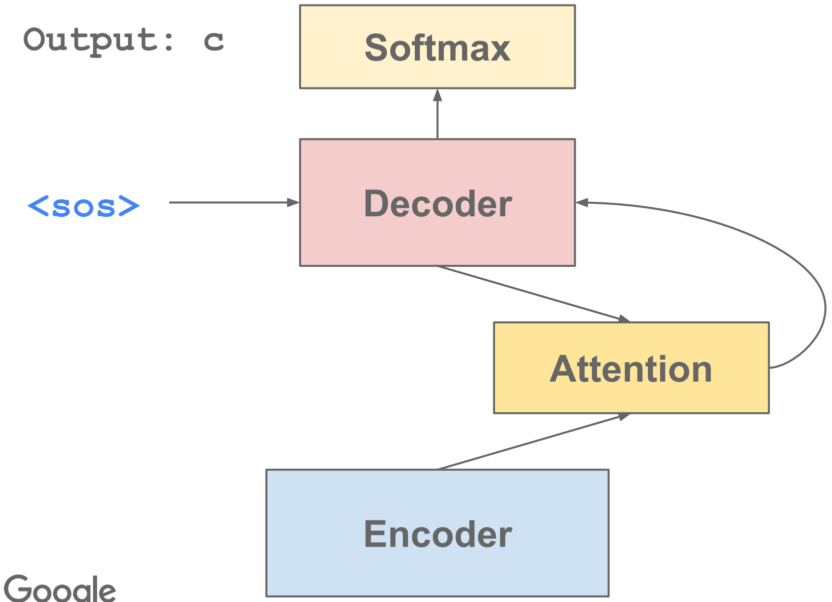


Reproduced from [Chan et al., 2015]

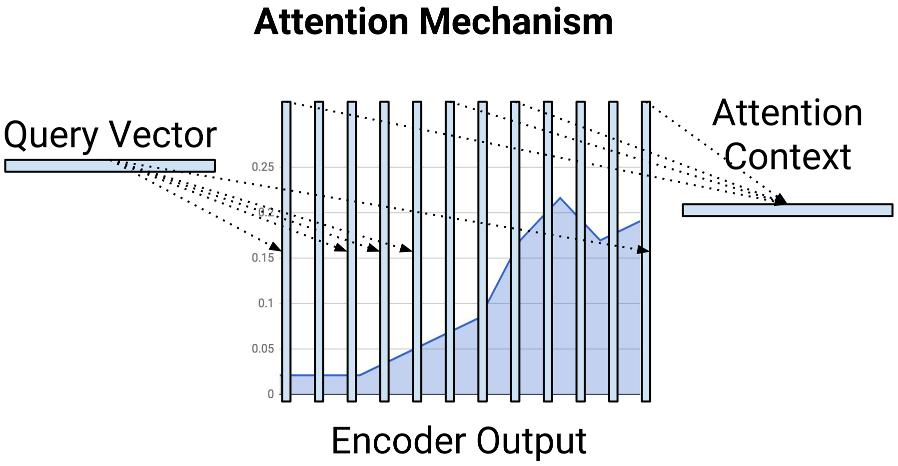
Attention-based Models

```
P(a|<sos>,x) = 0.01
P(b|<sos>,x) = 0.01
```
`P(c|<sos>,x) = 0.92`

...

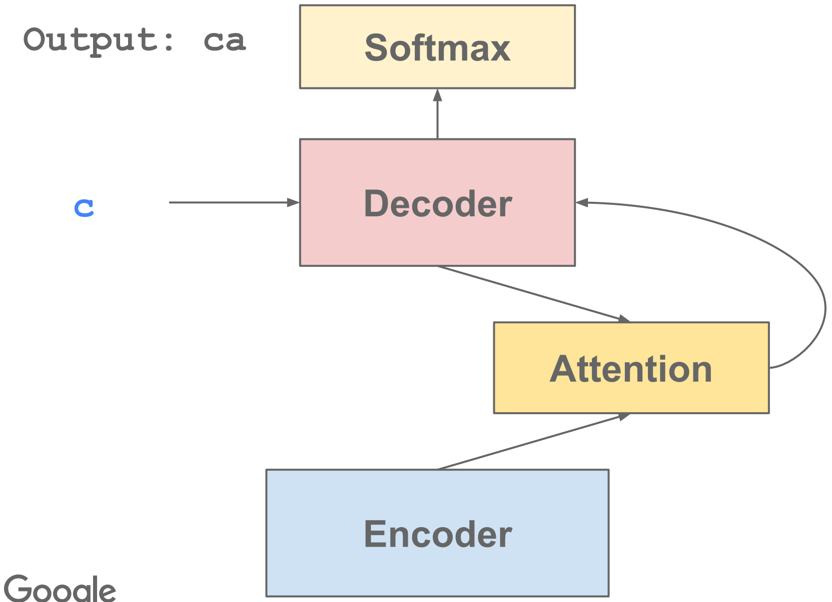


Attention mechanism summarizes encoder features relevant to predict next label



Attention-based Models

P(a|c,<sos>,x) = 0.95
P(b|c,<sos>,x) = 0.01
P(c|c,<sos>,x) = 0.01
...

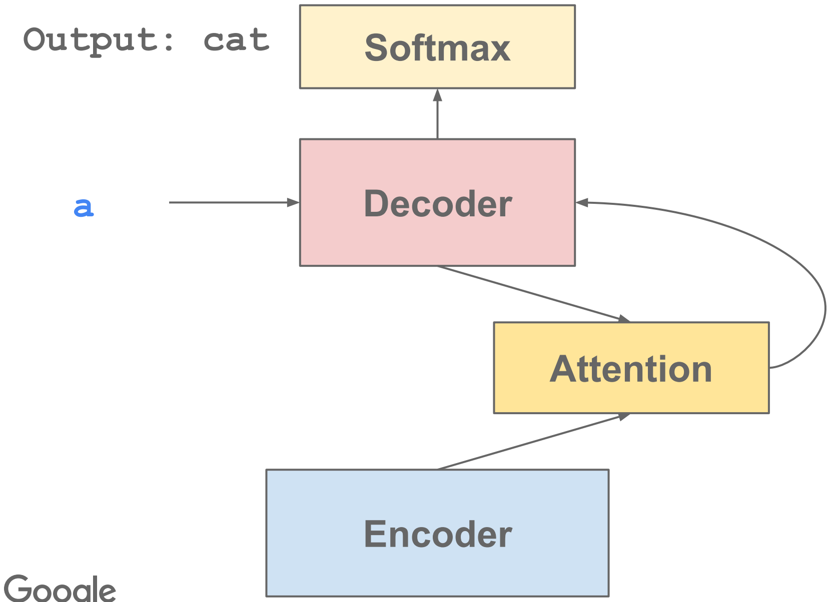


Labels from previous step are fed into decoder at the next step to predict

$$P(\mathbf{y}_u | y_{u-1}, \cdots, y_0, \mathbf{x})$$

Attention-based Models

```
P(a|a,c,<sos>,x) = 0.01
P(b|a,c,<sos>,x) = 0.08
       ...
P(t|a,c,<sos>,x) = 0.89
       ...
```



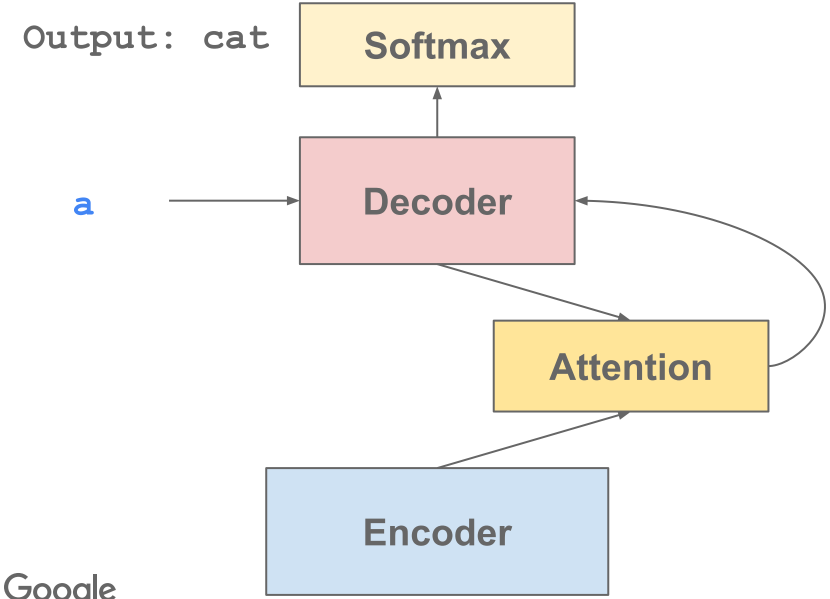
Labels from previous step are fed into decoder at the next step to predict

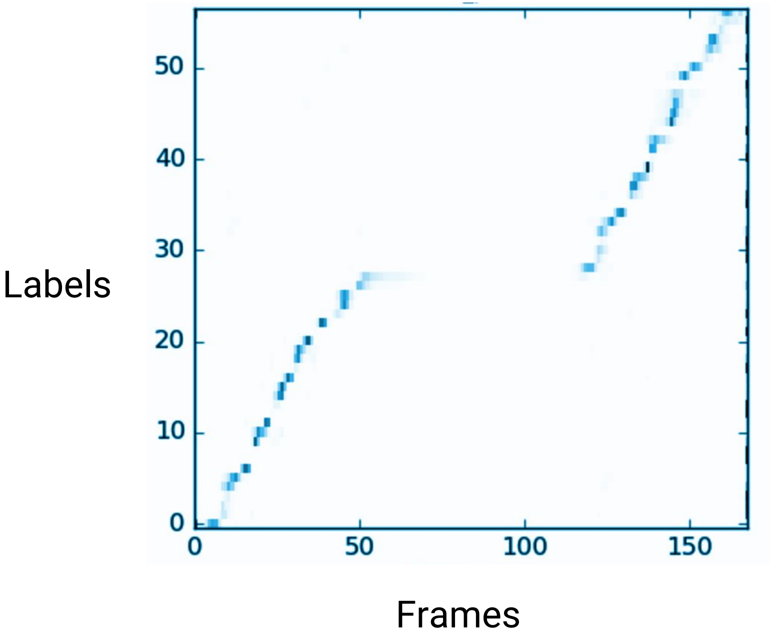
$$P(\mathbf{y}_u | y_{u-1}, \cdots, y_0, \mathbf{x})$$

Attention-based Models

```
P(a|t,a,c,<sos>,x) = 0.01
P(b|t,a,c,<sos>,x) = 0.01
...
P(<eos>|t,a,c,<sos>,x) = 0.96
...
```

Process terminates when the model predicts <eos> which denotes end of sentence.

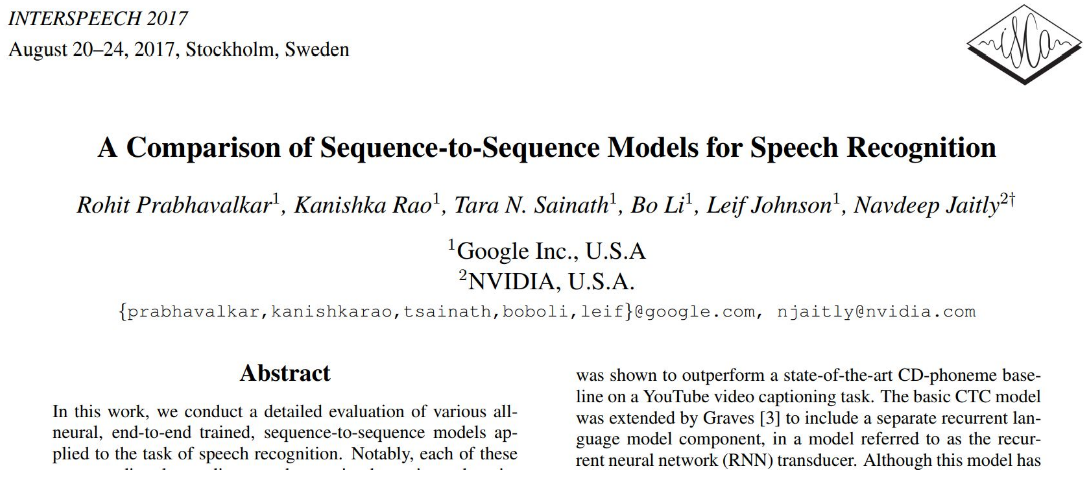




Comparing Various Approaches: Case-Study on a 12,500 hour Google Task

Comparing Various End-to-End Approaches

- Compare various sequence-to-sequence models head-to-head, trained on same data, to understand how these approaches compare to each other
- Evaluated on a large-scale 12,500 hour Google Voice Search Task


INTERSPEECH 2017
August 20–24, 2017, Stockholm, Sweden

A Comparison of Sequence-to-Sequence Models for Speech Recognition

Rohit Prabhavalkar[1], *Kanishka Rao*[1], *Tara N. Sainath*[1], *Bo Li*[1], *Leif Johnson*[1], *Navdeep Jaitly*[2†]

[1]Google Inc., U.S.A
[2]NVIDIA, U.S.A.

{prabhavalkar,kanishkarao,tsainath,boboli,leif}@google.com, njaitly@nvidia.com

Abstract

In this work, we conduct a detailed evaluation of various all-neural, end-to-end trained, sequence-to-sequence models applied to the task of speech recognition. Notably, each of these

was shown to outperform a state-of-the-art CD-phoneme baseline on a YouTube video captioning task. The basic CTC model was extended by Graves [3] to include a separate recurrent language model component, in a model referred to as the recurrent neural network (RNN) transducer. Although this model has

[Prabhavalkar et al., 2017]

Experimental Setup: Model Configuration

- ## Baseline
  - State-of-the-art CD-Phoneme model: 5x700 BLSTM; ~8000 CD-Phonemes
  - CTC-training followed by sMBR discriminative sequence training
  - Decoded with large 5-gram LM in first pass
  - Second pass rescoring with much larger 5-gram LM in second pass
  - Lexicon of millions of words of expert curated pronunciations
- ## Sequence-to-Sequence Models
  - Trained to output graphemes: [a-z], [0-9], <space>, and punctuation
  - Models are evaluated using beam search (Keep Top 15 Hyps at Each Step)
  - ***Models are not decoded or rescored with an external language model, or a pronunciation model***

Experimental Setup: Data

- Training Set
  - ~15M Utterances (~12,500 hrs) of anonymized utterances from Google Voice Search Traffic
  - Multi-style Training: Artificially distorted using room simulator by adding noise samples extracted from YouTube videos and environmental recordings of daily events
- Evaluation Sets
  - Dictation: ~13K utterances (~124K words) open-ended dictation
  - VoiceSearch: ~12.9K utterances (~63K words) of voice-search queries

Results

Model	Clean	
	Dictation	VoiceSearch
Baseline Uni. Context Dependent Phones (CDP)	6.4	9.9
Baseline BiDi. CDP	**5.4**	**8.6**
CTC-grapheme	39.4	53.4

Decoding CTC-grapheme models without an LM performs poorly

Results

Model	Clean	
	Dictation	VoiceSearch
Baseline Uni. CDP	6.4	9.9
Baseline BiDi. CDP	**5.4**	**8.6**
CTC-grapheme	39.4	53.4
RNN-T	6.6	12.8

RNN-T which augments CTC with a neural LM significantly improves performance, and is close to the unidirectional baseline

Results

Model	Clean	
	Dictation	VoiceSearch
Baseline Uni. CDP	6.4	9.9
Baseline BiDi. CDP	**5.4**	**8.6**
CTC-grapheme	39.4	53.4
RNN-T	6.6	12.8
Attention-based Model	6.6	11.7

Attention-based model performs the best, but cannot be used for streaming speech recognition

Comparison of End-to-End Approaches [Battenberg et al., 2017]

	Architecture	SWBD WER	CH WER
Published	Iterated-CTC [29]	11.3	18.7
	BLSTM + LF MMI [21]	8.5	15.3
	LACE + LF MMI [4] [28]	8.3	14.8
	Dilated convolutions [25]	7.7	14.5
	CTC + Gram-CTC [17]	7.3	14.7
	BLSTM + Feature fusion[23]	**7.2**	**12.7**
Ours	CTC [17]	9.0	17.7
	RNN-Transducer		
	Beam Search **NO LM**	8.5	16.4
	Beam Search + LM	8.1	17.5
	Attention		
	Beam Search **NO LM**	8.6	17.8
	Beam Search + LM	8.6	17.8

Switchboard

Model	Dev	Test
CTC [4]		
Greedy decoding	23.03	-
Beam search + LM (beam=2000)	15.9	16.44
RNN-Transducer		
Greedy decoding	18.99	-
Beam search (beam=32)	17.41	-
+ LM rescoring	15.6	16.50
Attention		
Greedy decoding	22.67	-
Beam search (beam=256)	18.71	-
+ Length-norm weight	19.5	-
+ Coverage cost	18.9	-
+ LM rescoring	16.0	16.48

DeepSpeech

Similar conclusions were reported by [Battenberg et al., 2017] on Switchboard. RNN-T without an LM is consistently better than CTC with an LM.

Combining Approaches

- Various end-to-end approaches can be successfully combined to improve the overall system
- CTC and Attention-based models can be combined in a multi-task learning framework [Kim et al., 2017]
- RNN-T can be augmented with an attention module which can
  - condition the language model component on the acoustics [Prabhavalkar et al., 2017] or,
  - be used to bias the decoder towards particular items of interest [He et al., 2017]
- An attention model can be augmented with a secondary attention module which can bias towards an arbitrary number of phrases of interest [Pundak et al., 2018] (will be discussed in more detail in a few slides)

Turning Research Into Reality

Google

Moving From Research To Reality

- In order to use an end-to-end model for real-world applications, we need
  - Performance that matches that of a conventional model
    - Including MWER Training
    - Including External Language Model
    - More details in [Chiu et al., 2018]
  - Model must incorporate contextual biasing to long-tail words
  - Model must be streaming

MWER Training
[Prabhavalkar et al., 2018]

Google

MWER Training of LAS Models: Motivation

- Attention-based Sequence-to-Sequence models are typically trained by optimizing cross entropy loss (i.e., maximizing log-likelihood of the training data)

$$\mathcal{L}_{\text{CE}} = \sum_{(\mathbf{x},\mathbf{y}^*)} \sum_{u=1}^{L+1} - \log P(y_u^* | y_{u-1}^*, \cdots, y_0^* = \langle \text{sos} \rangle, \mathbf{x})$$

- Training criterion does not match metric of interest: Word Error Rate
- Goal: Optimize a loss that minimizes or is correlated with minimizing word error rate

MWER Training of LAS Models: Motivation

- Proposal: Minimize Expected Word Error Rate (MWER)
  - In the context of conventional ASR system, for Neural Network Acoustic Models
    - State-level Minimum Bayes Risk (sMBR) [Kingsbury, 2009]
    - Word-level edit-based Minimum Bayes Risk (EMBR) [Shannon, 2017]
  - In the context of end-to-end models
    - Connectionist Temporal Classification (CTC) [Graves and Jaitly, 2014]
    - Recurrent Neural Aligner (RNA) [Sak et al., 2017]: Applies word-level EMBR to RNA
    - Machine Translation:
      - REINFORCE [Ranzato et al., 2016]
      - Beam Search Optimization [Wiseman and Rush, 2016]
      - Actor-Critic [Bahdanau et al., 2017]

MWER Training of LAS Models

$$\mathcal{L}_{\text{werr}}(\mathbf{x}, \mathbf{y}^*) = \mathbb{E}[\boxed{\mathcal{W}(\mathbf{y}, \mathbf{y}^*)}] = \sum_{\mathbf{y}} P(\mathbf{y}|\mathbf{x})\mathcal{W}(\mathbf{y}, \mathbf{y}^*)$$

Number of Word Errors

Minimizing expected WER directly is intractable since it involves a summation over all possible label sequences

MWER Training: Approximating expectation by sampling from the model

Google

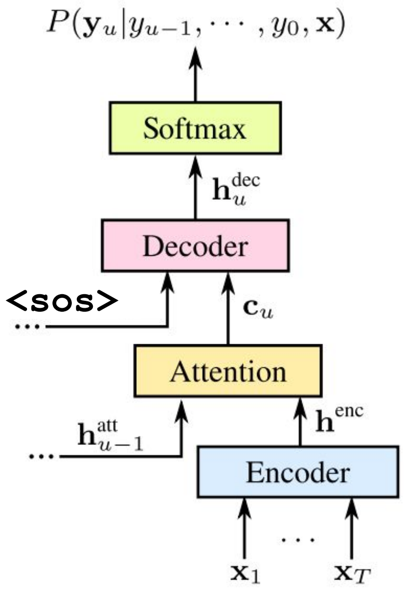
Approximation By Sampling [Shannon, 17]

$$\mathcal{L}_{\text{werr}}(\mathbf{x}, \mathbf{y}^*) = \mathbb{E}[\mathcal{W}(\mathbf{y}, \mathbf{y}^*)] = \sum_{\mathbf{y}} P(\mathbf{y}|\mathbf{x})\mathcal{W}(\mathbf{y}, \mathbf{y}^*)$$

$$\approx \mathcal{L}_{\text{werr}}^{\text{Sample}}(\mathbf{x}, \mathbf{y}^*) = \frac{1}{N} \sum_{\mathbf{y}_i \sim P(\mathbf{y}|\mathbf{x})} \mathcal{W}(\mathbf{y}_i, \mathbf{y}^*)$$

Approximate expectation using samples.

Approximation By Sampling [Shannon, 17]



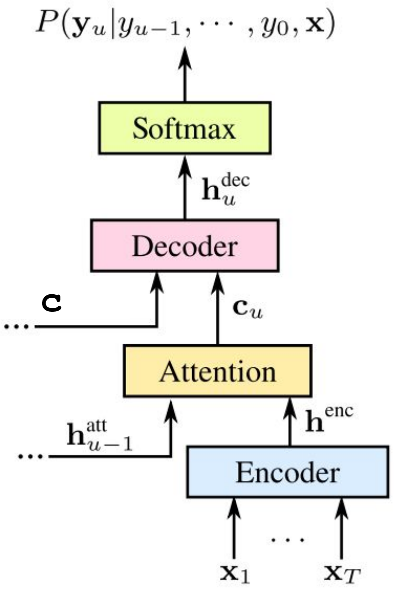
c

```
P(a|<sos>,x)  = 0.01
P(b|<sos>,x)  = 0.01
P(c|<sos>,x)  = 0.81
P(d|<sos>,x)  = 0.02
P(e|<sos>,x)  = 0.01
P(f|<sos>,x)  = 0.08
       .
       .
       .
```

Sample c

Drawing samples is particularly easy for locally-normalized models such as LAS!

Approximation By Sampling [Shannon, 17]



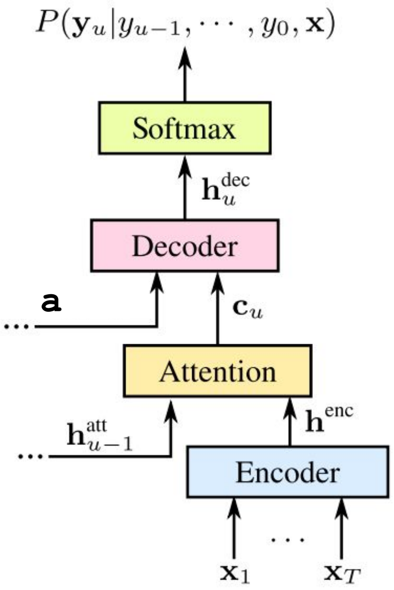
ca

P(a|c,<sos>,x) = 0.61
P(b|c,<sos>,x) = 0.02
P(c|c,<sos>,x) = 0.01
P(d|c,<sos>,x) = 0.00
P(e|c,<sos>,x) = 0.26
P(f|c,<sos>,x) = 0.00
.
.
.

Sample a

Drawing samples is particularly easy for locally-normalized models such as LAS!

Approximation By Sampling [Shannon, 17]



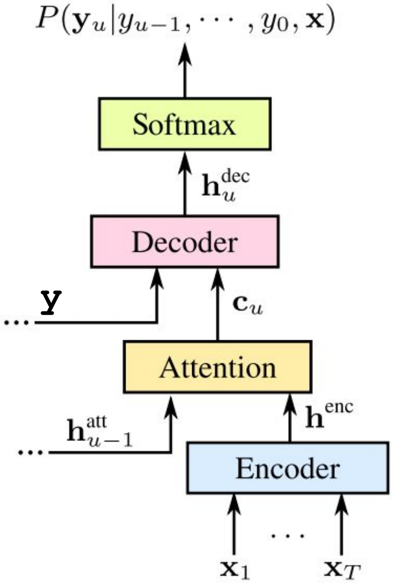
cab

P(a|a,c,<sos>,x) = 0.01
P(b|a,c,<sos>,x) = 0.41
P(c|a,c,<sos>,x) = 0.01
P(d|a,c,<sos>,x) = 0.51
P(e|a,c,<sos>,x) = 0.00
P(f|a,c,<sos>,x) = 0.00
.
.
.

Sample b

Drawing samples is particularly easy for locally-normalized models such as LAS!

Approximation By Sampling [Shannon, 17]



cabs in calgary <eos>

P(a|y,...,c,<sos>,x) = 0.00
P(b|y,...,c,<sos>,x) = 0.00

.
.
.

P(<eos>|y,...,c,<sos>,x)=0.98

Sample <eos>

Drawing samples is particularly easy for locally-normalized models such as LAS!

Approximation By Sampling [Shannon, 17]

$$\nabla \mathcal{L}_{\text{werr}}^{\text{Sample}}(\mathbf{x}, \mathbf{y}^*) = \sum_{\mathbf{y}} P(\mathbf{y}|\mathbf{x}) \left[\mathcal{W}(\mathbf{y}, \mathbf{y}^*) - \mathbb{E}[\mathcal{W}(\mathbf{y}, \mathbf{y}^*)]\right] \nabla \log P(\mathbf{y}|\mathbf{x})$$
$$\approx \frac{1}{N} \sum_{\mathbf{y}_i \sim P(\mathbf{y}|\mathbf{x})} [\mathcal{W}(\mathbf{y}_i, \mathbf{y}^*) - \widehat{\mathcal{W}}] \nabla \log P(\mathbf{y}|\mathbf{x}) \qquad (6)$$

Gradient itself is an expectation, which can be approximated using samples!

Approximation By Sampling [Shannon, 17]

$$\nabla \mathcal{L}^{\text{Sample}}_{\text{werr}}(\mathbf{x}, \mathbf{y}^*) = \sum_{\mathbf{y}} P(\mathbf{y}|\mathbf{x}) \left[\mathcal{W}(\mathbf{y}, \mathbf{y}^*) - \mathbb{E}[\mathcal{W}(\mathbf{y}, \mathbf{y}^*)]\right] \nabla \log P(\mathbf{y}|\mathbf{x})$$

$$\approx \frac{1}{N} \sum_{\mathbf{y}_i \sim P(\mathbf{y}|\mathbf{x})} \boxed{[\mathcal{W}(\mathbf{y}_i, \mathbf{y}^*) - \widehat{\mathcal{W}}]} \nabla \log P(\mathbf{y}|\mathbf{x}) \qquad (6)$$

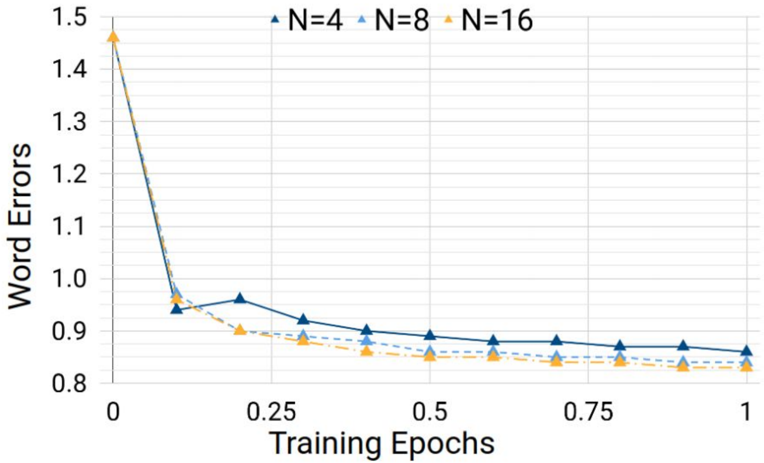
Increase the probability of sequences which have lower than average number of word errors!

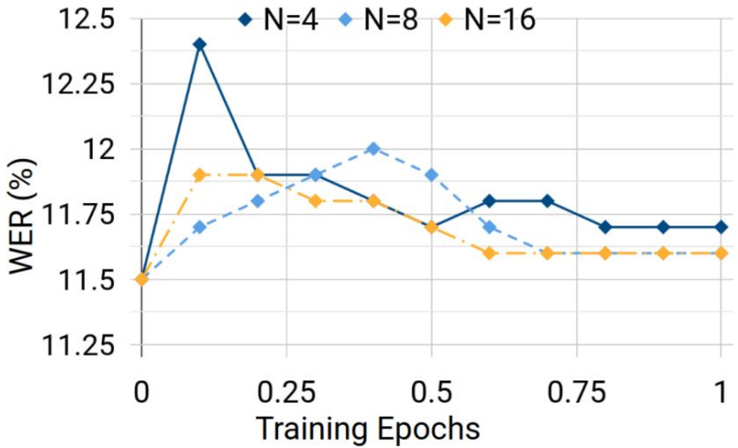
Approximation By Sampling [Shannon, 17]

$$\mathcal{L}^{\text{Sample}} = \sum_{(\mathbf{x},\mathbf{y}^*)} \mathcal{L}^{\text{Sample}}_{\text{werr}}(\mathbf{x}, \mathbf{y}^*) + \lambda \mathcal{L}_{\text{CE}}$$

Interpolate with CE-loss to stabilize training.
F-smoothing or H-criterion [Su et al., 2013]

Approximation By Sampling [Shannon, 17]





- Why doesn't the sampling-based approximation "work"?
    - Mismatch between decoding process during training (sampling) and decoding criterion (beam search) which focuses heavily on top hypotheses at each step [Kim and Rush, 2016]
    - In [Shannon, 17], paths are sampled from the lattice which corresponds to the most likely hypotheses, not from the space of all word sequences

MWER Training: Approximating expectation using decoded N-Best List

Approximation using N-Best List [Stolcke+,97][Povey,03]

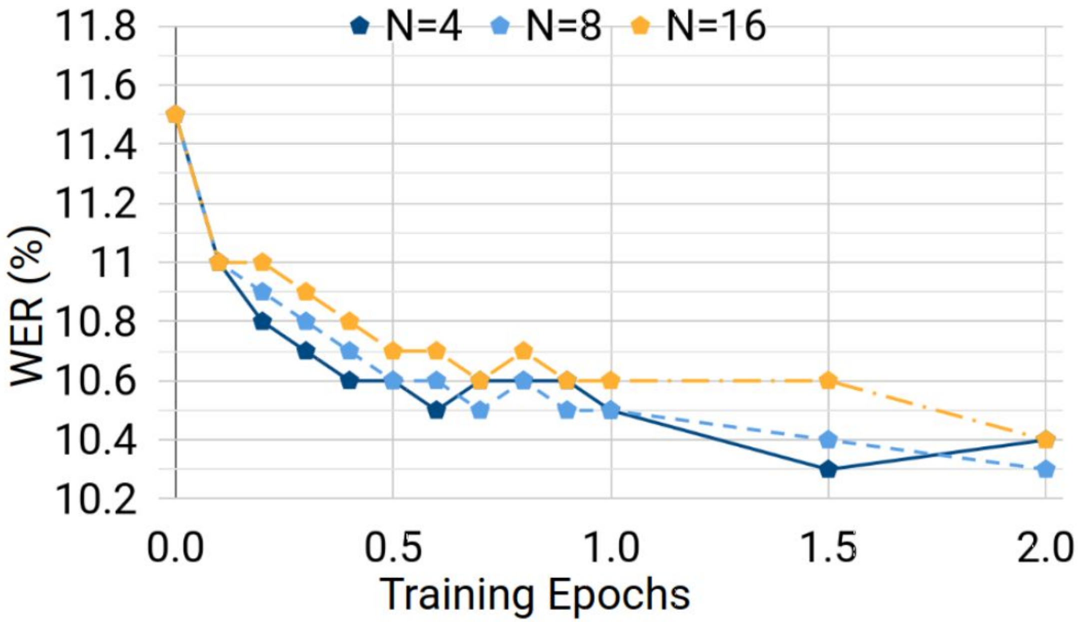
$$\mathcal{L}_{\text{werr}}(\mathbf{x}, \mathbf{y}^*) = \mathbb{E}[\mathcal{W}(\mathbf{y}, \mathbf{y}^*)] = \sum_{\mathbf{y}} P(\mathbf{y}|\mathbf{x})\mathcal{W}(\mathbf{y}, \mathbf{y}^*)$$

$$\mathcal{L}_{\text{werr}}^{\text{N-best}}(\mathbf{x}, \mathbf{y}^*) = \sum_{\mathbf{y}_i \in \text{Beam}(\mathbf{x}, N)} \widehat{P}(\mathbf{y}_i|\mathbf{x}) \left[\mathcal{W}(\mathbf{y}_i, \mathbf{y}^*) - \widehat{W}\right]$$

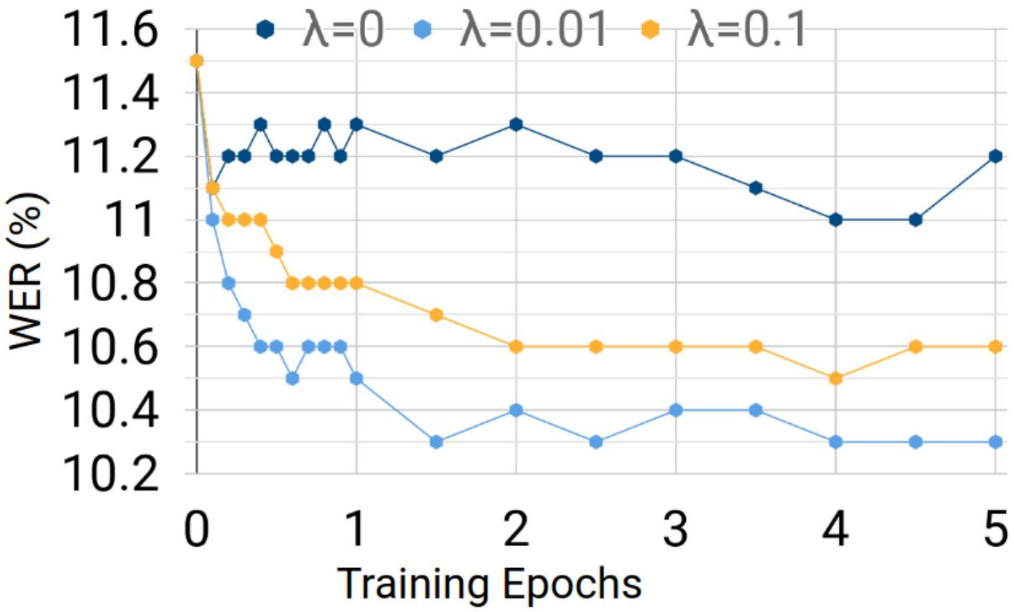
$$\widehat{P}(\mathbf{y}_i|\mathbf{x}) = \frac{P(\mathbf{y}_i|\mathbf{x})}{\sum_{\mathbf{y}_i \in \text{Beam}(\mathbf{x}, N)} P(\mathbf{y}_i|\mathbf{x})}$$

Assume that probability distribution is concentrated on top-N hypotheses

Approximation using N-Best List [Stolcke+,97][Povey,03]



Approximation using N-Best List [Stolcke+,97][Povey,03]



$$\mathcal{L}^{\text{N-best}} = \sum_{(\mathbf{x},\mathbf{y}^*)} \mathcal{L}^{\text{N-best}}_{\text{werr}}(\mathbf{x}, \mathbf{y}^*) + \lambda \mathcal{L}_{\text{CE}}$$

Impact of interpolating MWER loss with CE loss during training.

Results: WER on Voice-Search Test Set

Model	Uni-Directional Encoder	Bi-Directional Encoder
Baseline	8.1	7.2
+MWER Training	**7.5 (7.4%)**	**6.9 (4.2%)**

Results after direct decoding (beam size=8)

Results: WER on Voice-Search Test Set

Model	Uni-Directional Encoder	Bi-Directional Encoder
Baseline	8.1	7.2
+MWER Training	**7.5 (7.4%)**	**6.9 (4.2%)**

Model + Second-Pass Rescoring	Uni-Directional Encoder	Bi-Directional Encoder
Baseline	7.3	6.6
+MWER Training	**6.7 (8.2%)**	**6.2 (6.1%)**

Results after N-best rescoring with Second-pass LM

MWER: Additional Comments

- Since [Prabhavalkar et al., 2018] we have repeated the experiments with MWER training on a number of models including RNN-T [Graves et al., 2013] and other streaming attention-based models such as MoChA [Chiu and Raffel, 2017] and the Neural Transducer [Jaitly et al., 2016]
- In all cases we have observed between 8% to 20% relative WER reduction
- Implementing MWER requires the ability to decode N-best hypotheses from the model which can be somewhat computationally expensive

Results: LAS Model on Librispeech (960 hour task)

Model	Dev	DevOther	Test	TestOther
CE Baseline	5.8	16.1	6.2	16.4
MWER	5.3 (-8.8%)	15.2 (-5.7%)	5.7 (-8.4%)	15.4 (-6.0%)

Librispeech models trained on full 960 hour training data, with 16K word piece targets. Models are evaluated without an LM.

Language Model

Google

Motivation #1

Reference	LAS model output
What language is built into electrical circuitry of a computer?	what language is built into electrical circuit tree of a computer
Leona Lewis believe	vienna lewis believe
Suns-Timberwolves score	sun's timberwolves score

Some Voice Search errors appear to be fixable with a good language model trained on more text-only data.

Google

Motivation #2

- The LAS model requires audio-text pairs: we have only 15M of these
- Our production LM is trained on billions of words of text-only data
- How can we look at incorporating a larger LM into our LAS model?
- More details can be found in [Kannan et al., 2018]

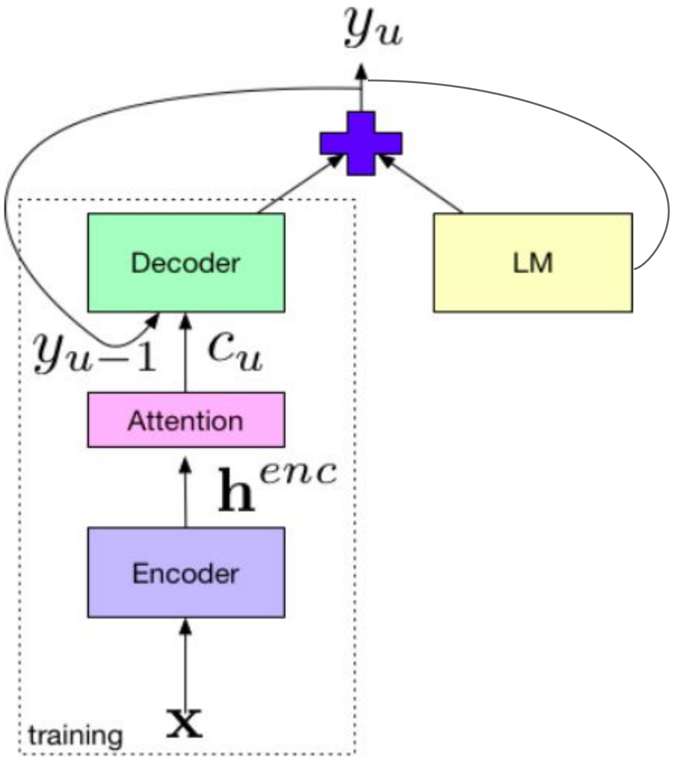
Shallow fusion

- Log-linear interpolation between language model and seq2seq model:

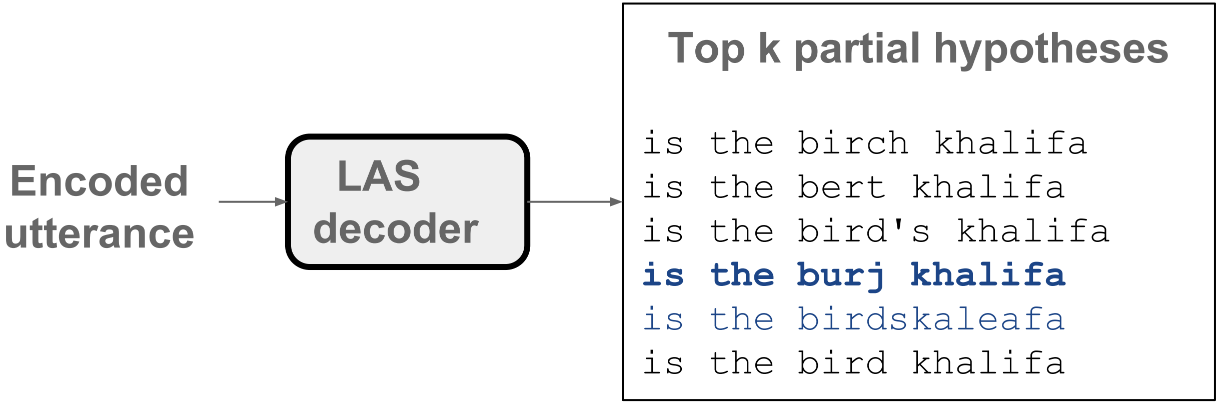
$$\mathbf{y}^* = \arg\max_y \log p(y|x) + \lambda \log p_{LM}(y)$$

- Typically only performed at inference time
- Language model is trained ahead of time and fixed
- LM can be either n-gram (FST) or RNN.
- Analogous to 1st pass rescoring.
- [Chorowski and Jaitly, 2017]. [Kannan et al., 2018].

Shallow fusion



Baseline LAS Model



Baseline LAS model relies on LM learned from train data

Baseline LAS Model

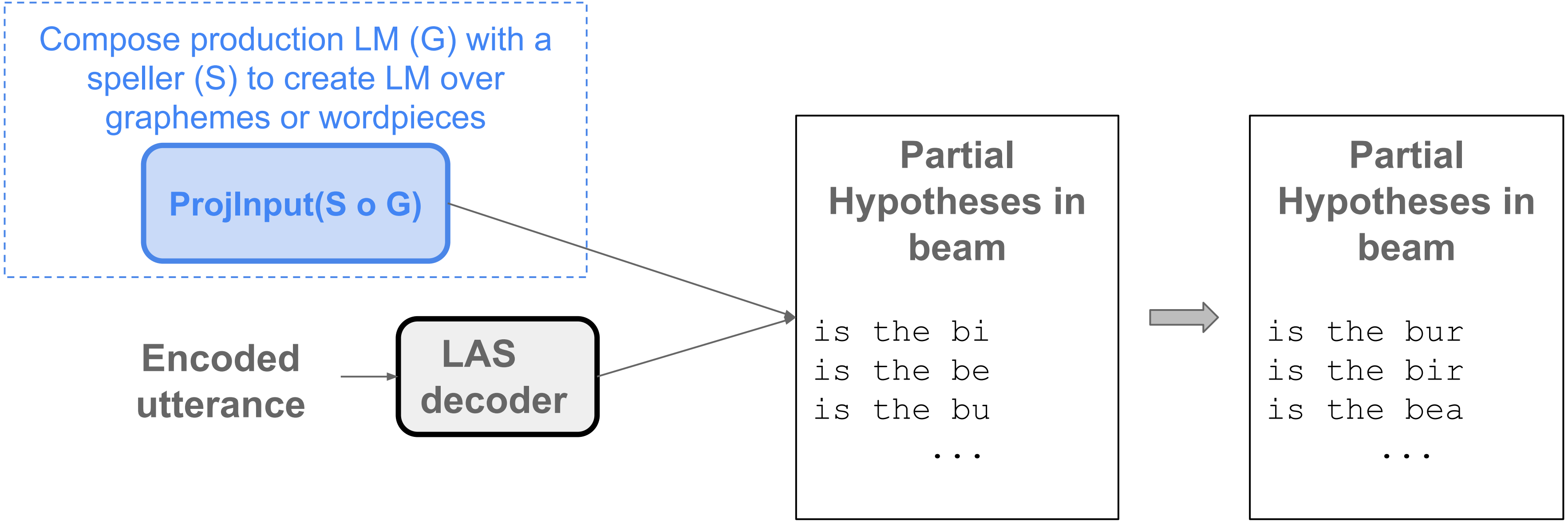
Encoded utterance → **LAS decoder** →

Top k partial hypotheses

```
is the birch khalifa
is the bert khalifa
is the bird's khalifa
is the burj khalifa
is the birdskaleafa
is the bird khalifa
```

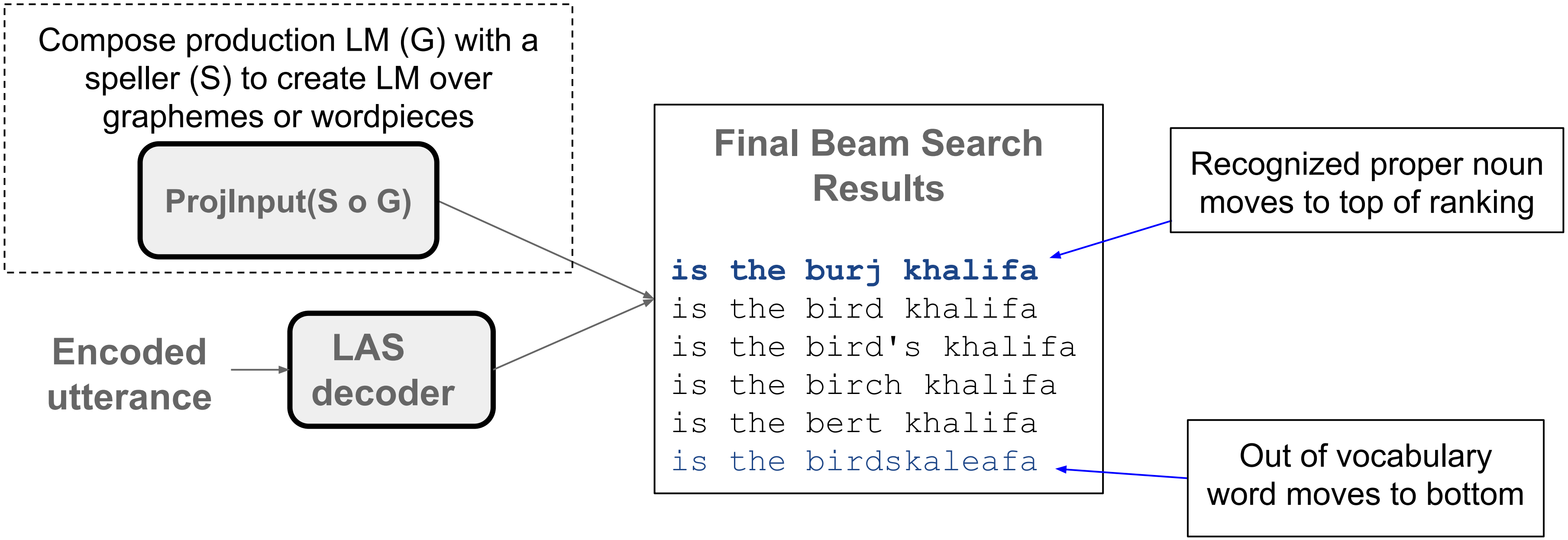
Unseen or rare phrases may be assigned low probability.

Integration with FST LM in 1st pass



Interpolate model posteriors with LM-score at *each* step of next label prediction

Integration with FST LM in 1st pass



Google

Results with FST LM

System	Dev WER	Test WER	LM Size
Baseline LAS	9.2%	7.7%	0 GB
LAS + FST LM in 1st pass	8.8%	7.4%	2 GB

Decoding with FST 1st pass production LMs into LAS system provides small improvement

Examples of LM wins

	Reference	Top 1 without LM	Top 1 with LM
Rare words	achondroplasia	acondra placia	achondroplasia
Proper nouns	st. isaac jogues mass schedule	st isaac jog's mass schedule	st isaac jogues mass schedule
	what causes high latency on a wi-fi connection?	what causes highlight and sienna wi-fi connection	what causes high latency on a wi-fi connection

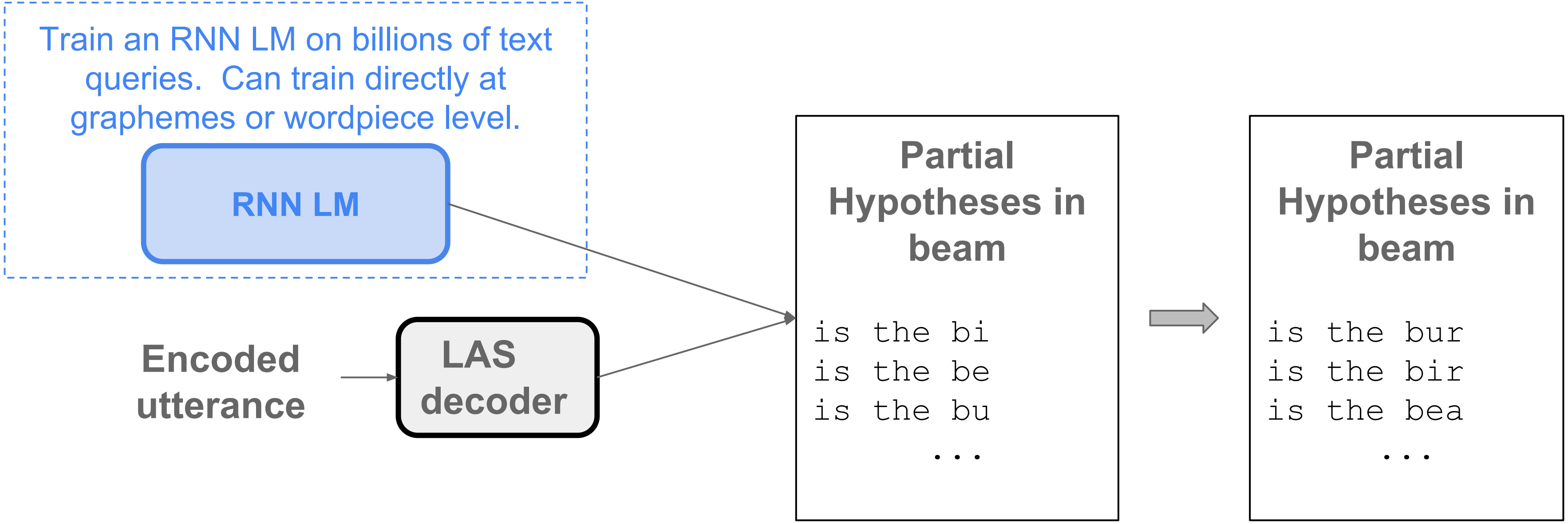
Decoding with LM can correct errors early in decoding.
In examples above, correct hypothesis does not appear in N-best without LM, so would not be possible to correct in second-pass with ProdLM.

Examples of LM losses

	Reference	Top 1 without LM	Top 1 with LM
Out of vocab terms	urgent important unurgent unimportant	urgent important unurgent unimportant	urgent important un urgent unimportant
Websites (specific type of OOV)	mathfunbook.com product of a power property	mathfunbook.com product of a power property	math funbook com product of a power property
Grammatically incorrect language	why you not listening to me tonight	why you not listening to me tonight	why are you not listening to me tonight

LAS model can actually output words it has never seen before.
Decoding with a language model removes this ability, costing about 0.2% absolute WER.

Alternative: integrate with RNN LM in 1st pass



RNN LM can achieve lower perplexity than *n*-gram LM and does not suffer from OOV problem.

Google

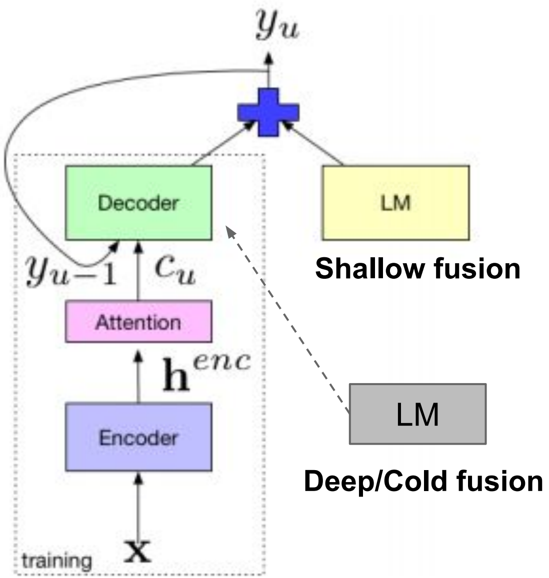
Results with RNN-LM

System	Dev WER	Test WER	LM Size
Baseline LAS	9.2%	7.7%	0 GB
LAS + FST LM in 1st pass	8.8%	7.4%	2 GB
LAS + RNN LM in 1st pass	**8.4%**	**7.0%**	**1 GB**

Decoding with RNN LM provides greater improvement at half the size!

Extending LAS with an LM

- Listen, Attend and Spell [Chan et al., 2015]
- How to incorporate an LM?
  - **Shallow fusion** [Kannan et al., 2018]
    - LM is applied on output
  - **Deep fusion** [Gulcehre et al., 2015]
    - Assumes LM is fixed
  - **Cold fusion** [Sriram et al., 2017]
    - Simple interface between a deep lm and the encoder
    - Allows to swap in task-specific LMs
- In these experiments, fusion is used during the beam search rather than n-best rescoring.



Comparison of Fusion Results

- Shallow Fusion still seems to perform the best
- Full comparison in [Toshniwal, 2018]

System	Voice Search	Dictation
Baseline LAS	5.6	4.0
Shallow Fusion	**5.3**	**3.7**
Deep Fusion	5.5	4.1
Cold Fusion	**5.3**	3.9

Handling Long Tail with Biasing

What is “Biasing”?

“An attempt to adapt the priors baked into the speech models to better model information gained between training and inference (aka context).”

Why Is Biasing Important

- Biasing can improve WER in domains by more than 10% relative

Test Set	WER, No Biasing	WER, Biasing
Contacts	15.0	2.8
Numeric	11.0	4.7
Yes-No-Cancel	18.8	10.4

How To Bias E2E Models

- Two options for biasing
  - Bias externally
  - Biasing within the model
- Paper reference [Pundak et al., 2018]
- In these experiments, we will evaluate on the following test sets
  - Contacts - “call Joe Doe, send a message to Jason Dean”
  - Songs - “play Lady Gaga, play songs from Jason Mraz”
  - Third Party - “text Jeanne, text John”

(1) Biasing - Shallow Fusion

- General equation for shallow fusion during beam search

$$\vec{y}^* = \arg\max_{\vec{y}} \log \underbrace{\boxed{P(\vec{y}|\vec{x})}}_{\text{E2E Model}} + \lambda \log \underbrace{\boxed{P_C(\vec{y})}}_{\text{Biasing FST}}$$

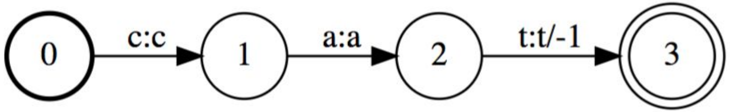
- Assumptions (for now)
    - Biasing is done at test time only
    - Tune interpolation weight λ per task

Biasing - Where to Apply Scores?

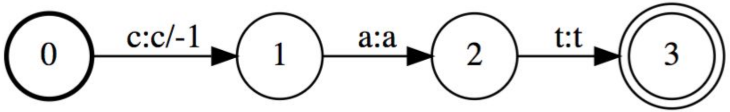
- Best to apply to every unit (E3)

Experiment	Method (Grapheme)	WER - Songs
E0	No Bias (LAS)	20.9
E1	LAS + End of Word Bias	19
E2	LAS + Beginning of Word Bias	16.5
E3	LAS + Every Subword Unit w/ Subtractive Cost Bias	13.4

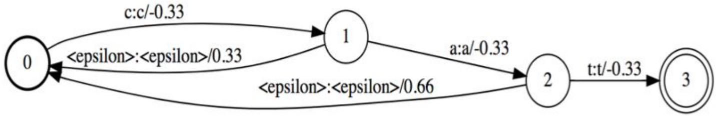
(a) End of Word Bias



(b) Beginning of Word Bias



(c) All Subword-Unit with Subtractive Cost Bias



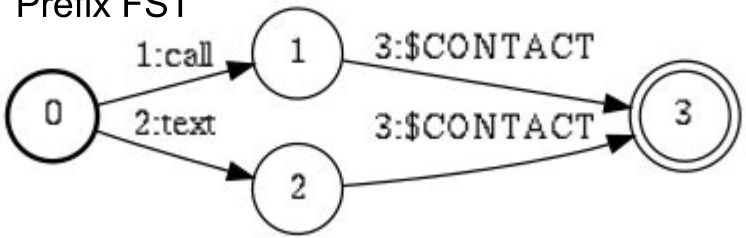
Improving Biasing Further

- Biasing FST should be applied before pruning the beam candidates, not rescoring a pruned beam (E4)
- Biasing at the WPM level is more effective than grapheme (E5)

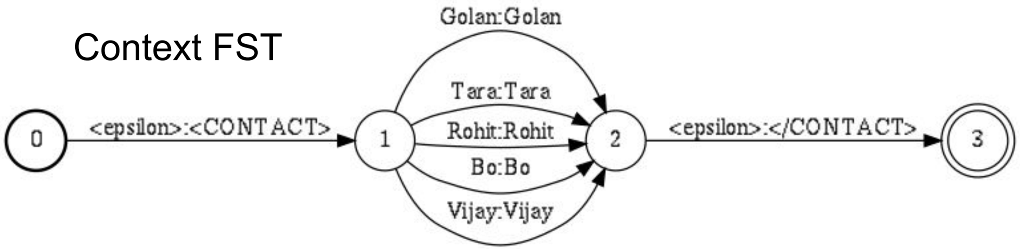
Experiment	Method (Grapheme)	WER - Songs
E0	No Bias (LAS)	20.9
E3	Grapheme Biasing	13.4
E4	Biasing Before Pruning	9.4
E5	4K Word Piece Model LAS Biasing	6.9

Prefixes & Suffixes

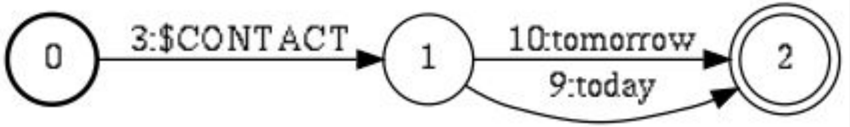
Prefix FST



Context FST

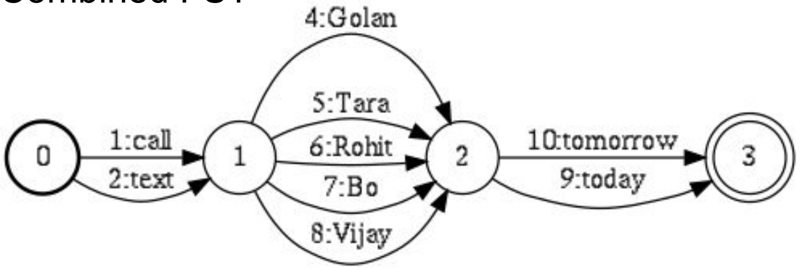


Suffix FST



- Since E2E model cannot predict $CONTACT, we prebuild individual FSTs into one.

Combined FST



Prefixes & Suffixes

- Using this makes a large difference for biasing

Experiment	Method (Grapheme)	WER - Songs
E0	No Bias (LAS)	20.9
E5	4K Word Piece Model LAS Biasing	6.9
E6	+ Prefix and Suffix	5.6

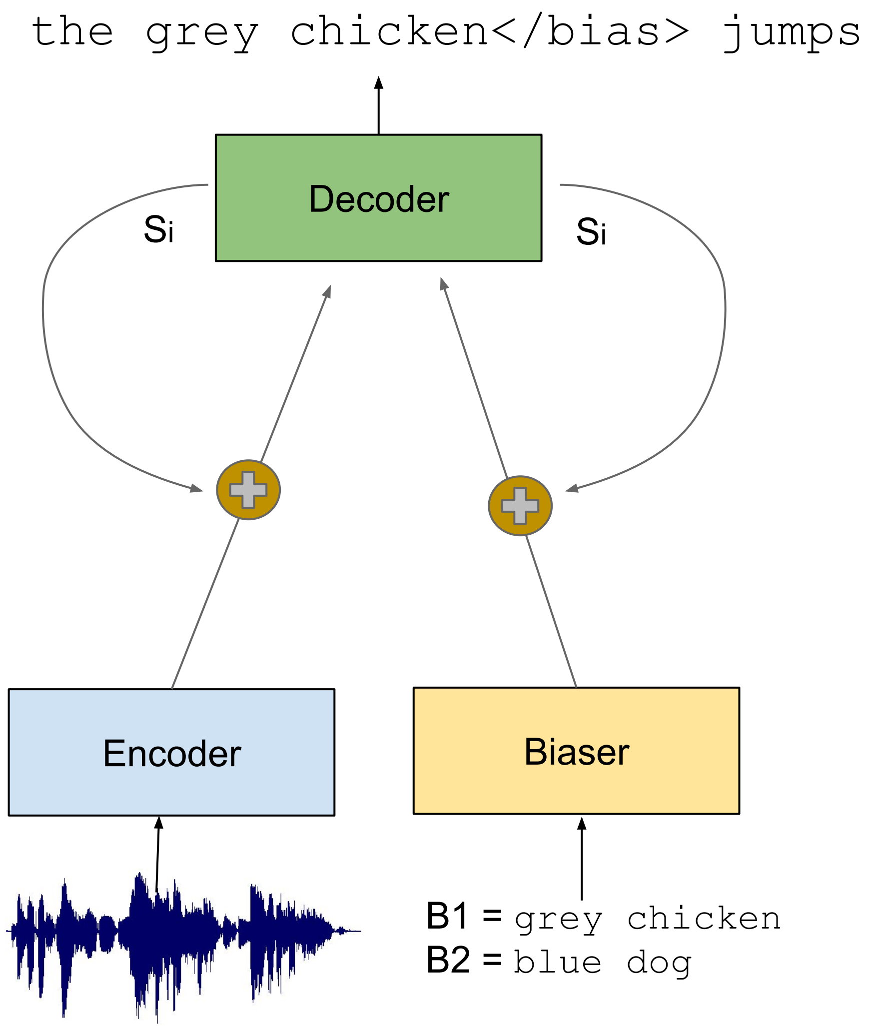
Shallow Fusion Biasing Summary

- Biasing E2E Models similar quality to conventional model

Method	CONTACTS	Songs	THIRD PARTY
Conventional Model No Biasing	36.1	26.5	-
Conventional Model Biasing	10.0	3.8	-
LAS No Biasing	26.9	16.8	10.5
LAS + Shallow Fusion, WPM 4K	7.1	5.6	**3.9**

(2) Biased LAS Model (CLAS)

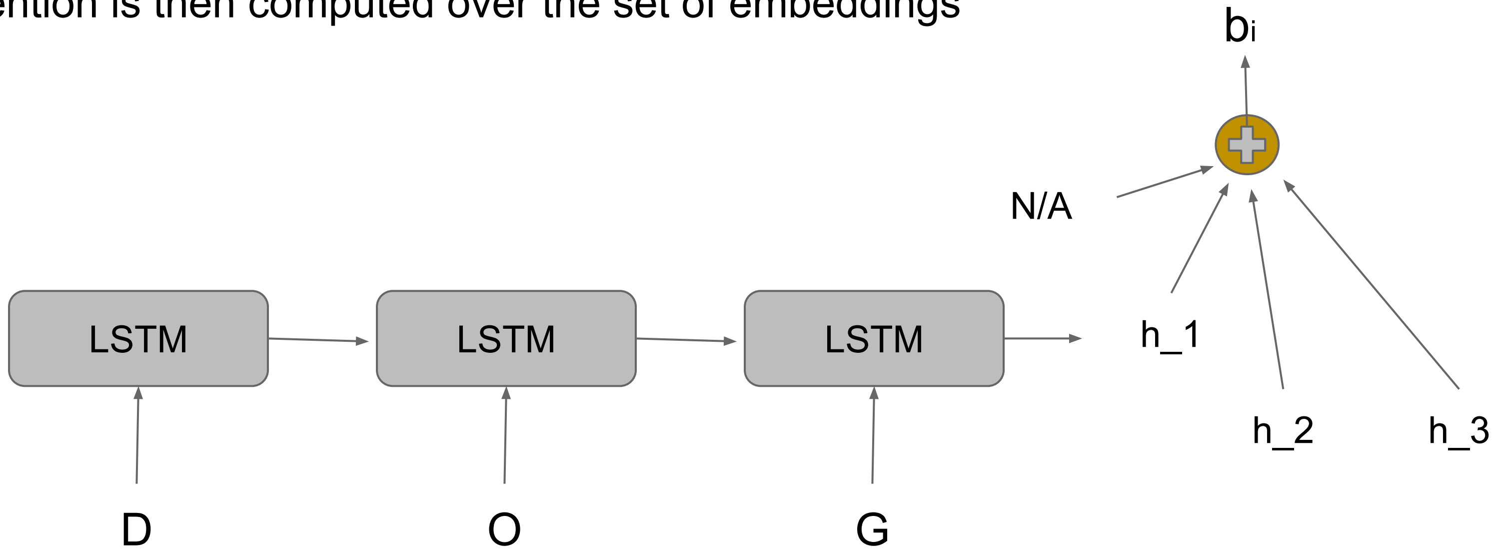
- Fixed-length embedding of bias phrases
- Attention over the embeddings, producing a **bias-dependent per-step** context vector
- Attention also includes a **N/A option** - don't apply bias

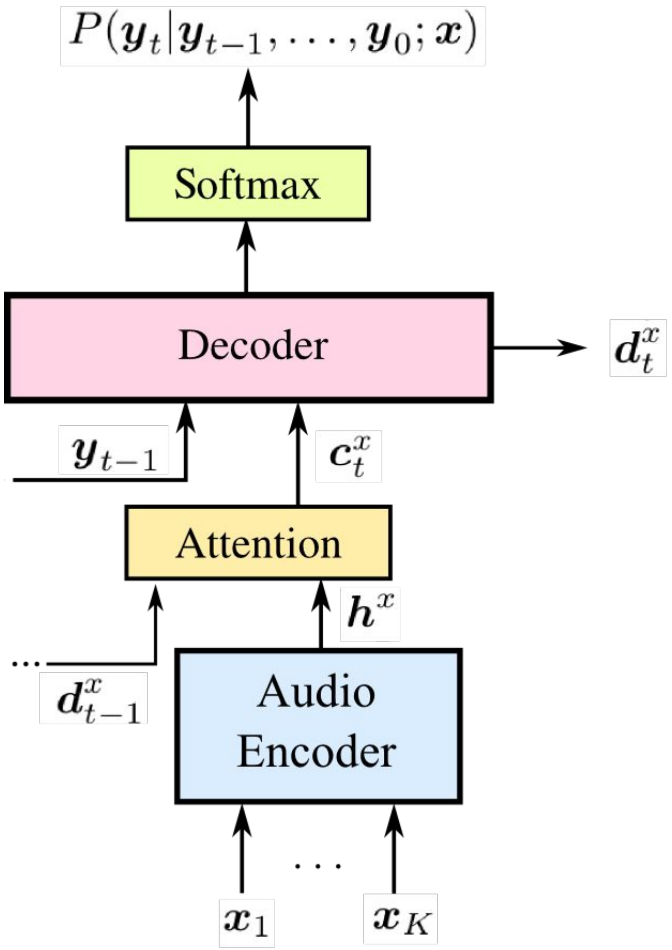


Google

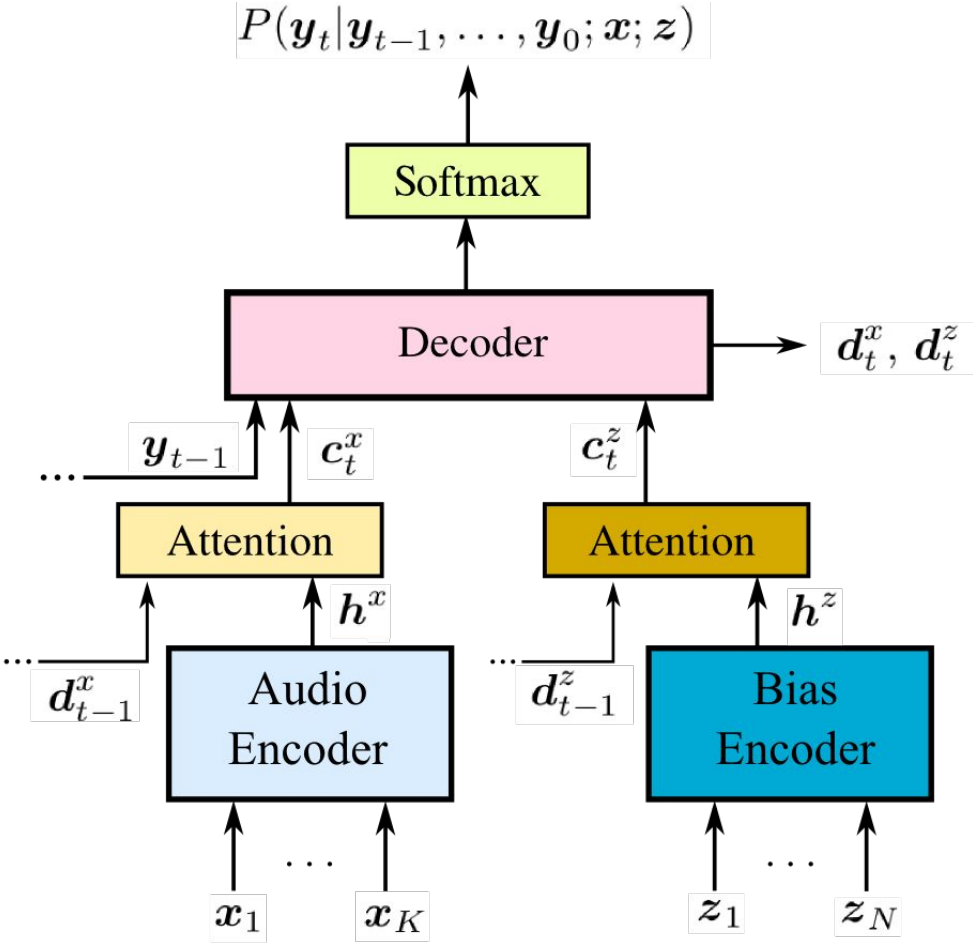
The Biaser

- The Biaser embeds each phrase into a fixed length vector
  - → Last state of an LSTM
- Embedding happens once per bias phrase (possibly offline)
  - Cheap computation
- Attention is then computed over the set of embeddings





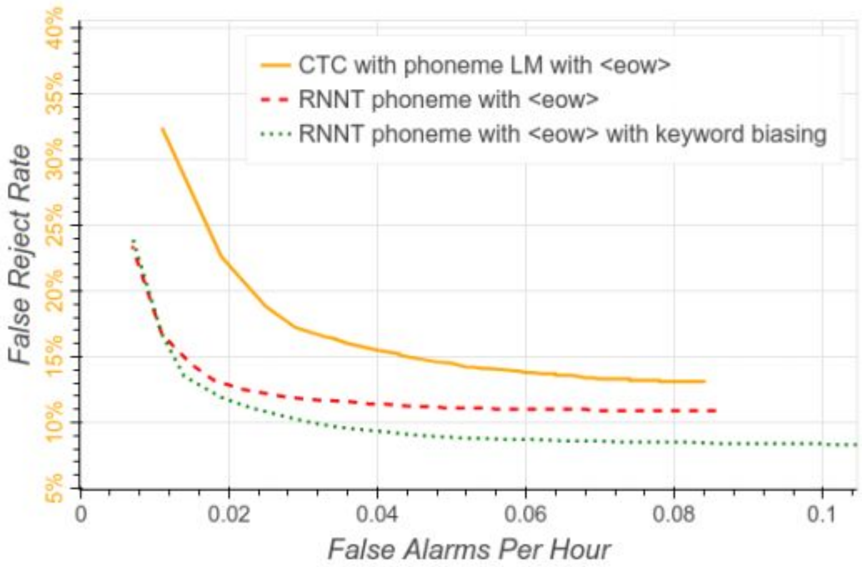
(a.) LAS Model

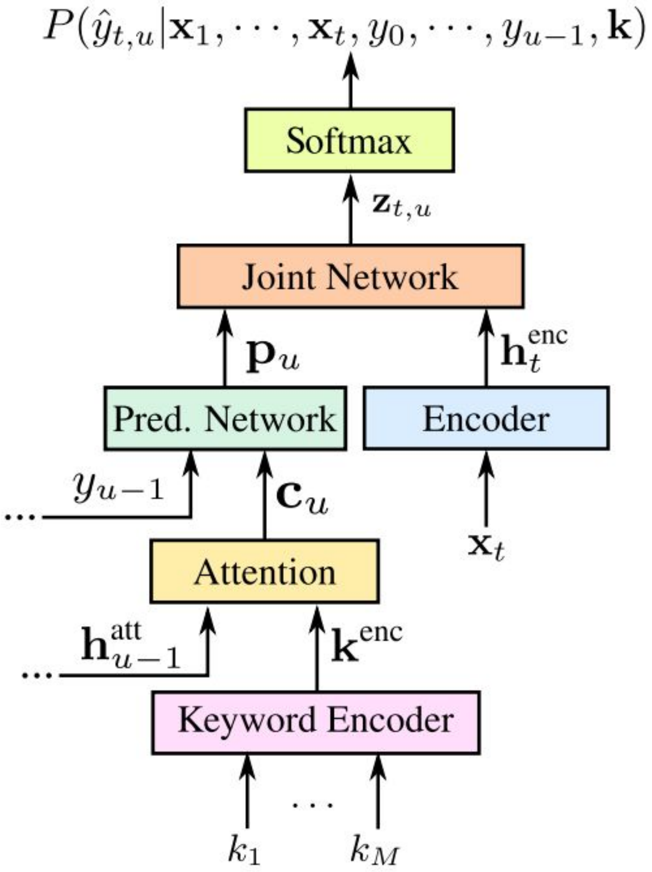


(b.) BLAS Model

Prior work: Keyword spotting with RNNT

- “Streaming Small-Footprint Keyword Spotting using Sequence-to-Sequence Models” [He et al., 2017]





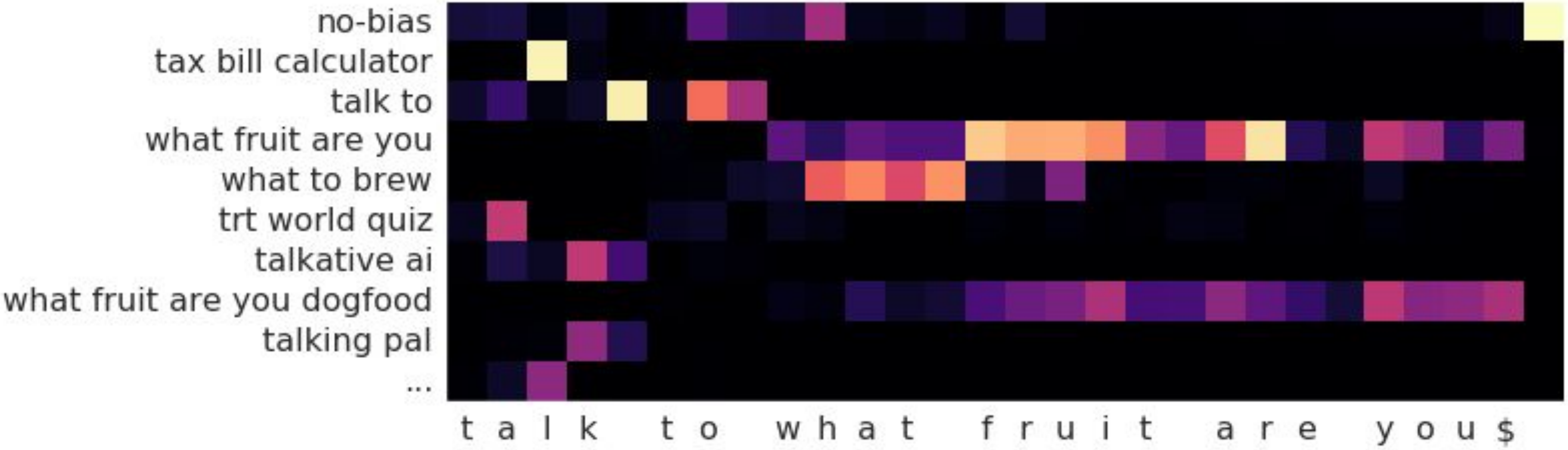
(c.) RNN-Transducer Biased with Attention Over Keyword.

CLAS training

- Example ref: `The grey chicken jumps over the lazy dog`
- Sample uniformly a bias phrase ***b***, e.g. `grey chicken`
- With **drop-probability** p (e.g. 0.5) drop the selected B and replace it with another bias phrase from the same batch
- Augment with additional N-1 more bias phrases from other references in the batch (distractors)
- Present the model the set of N (shuffled) bias phrases:
    - `quick turtle`
    - `grey chicken`
    - `brave monkey`
- If ***b*** was not dropped, insert a `</bias>` token to reference:
    - `The grey chicken</bias> jumps over the lazy dog`

Google

Biasing Example



Key aspects of CLAS

- Biasing is viewed as a keyword detection task which relates to both audio and LM (cf. beam search biasing)
- CLAS embeds “long” var-length bias sequences into fixed-length vectors
- CLAS computes attention over a set of phrases
- The model can take any list of bias phrases in inference time (including OOVs)
    - In training the bias phrases list is randomized for each batch
    - The number and content of bias phrases can be changed from training to inference

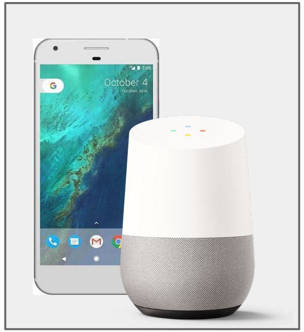
Biasing Summary

- CLAS model performs similar to biasing of conventional model

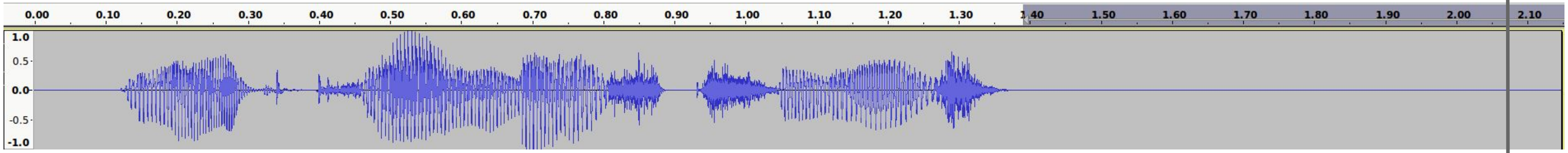
Method	CONTACTS	Songs	THIRD PARTY
Conventional Model No Biasing	36.1	26.5	-
Conventional Model Biasing	10.0	3.8	-
LAS No Biasing	26.9	16.8	10.5
CLAS + Shallow Fusion, Grapheme	7.5	5.7	5.6

Online Models

Streaming speech recognition

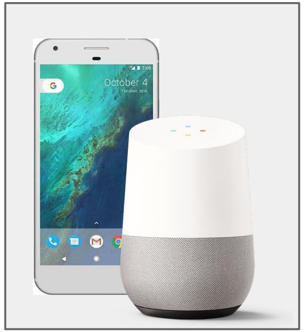


Finalize recognition &
Taking action / fetching the search results



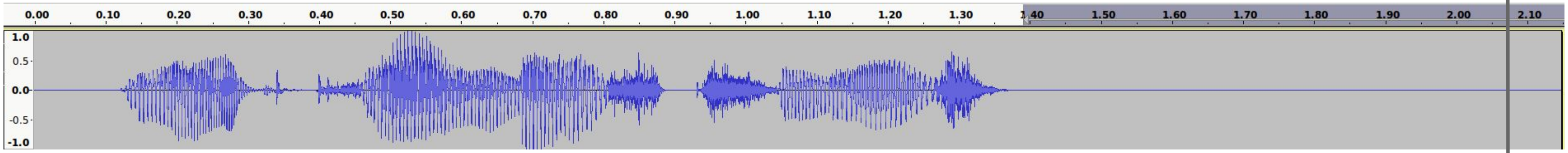
Recognize the audio

Streaming speech recognition



Finalize recognition &
Taking action / fetching the search results

Endpoint quickly

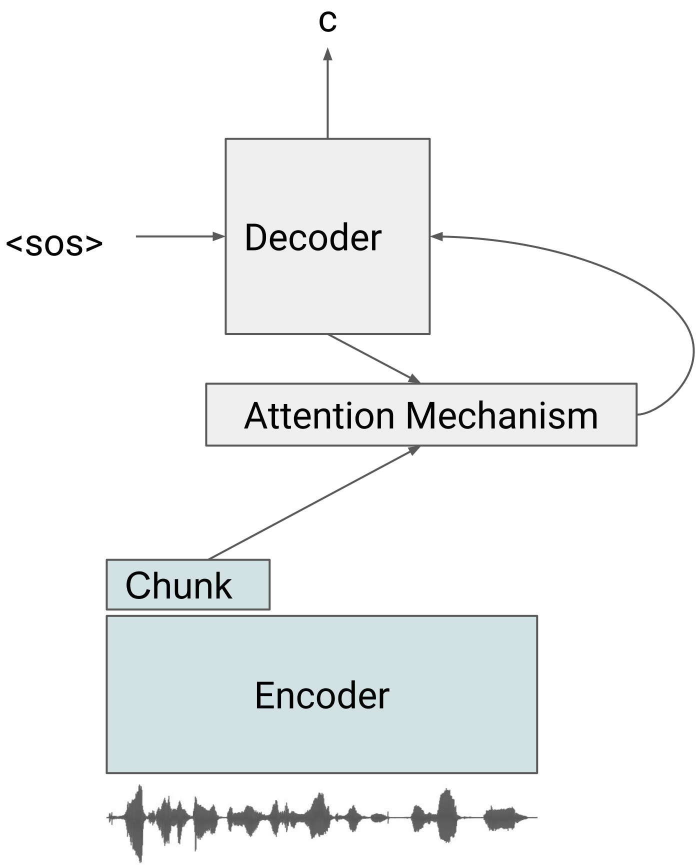


Recognize the audio

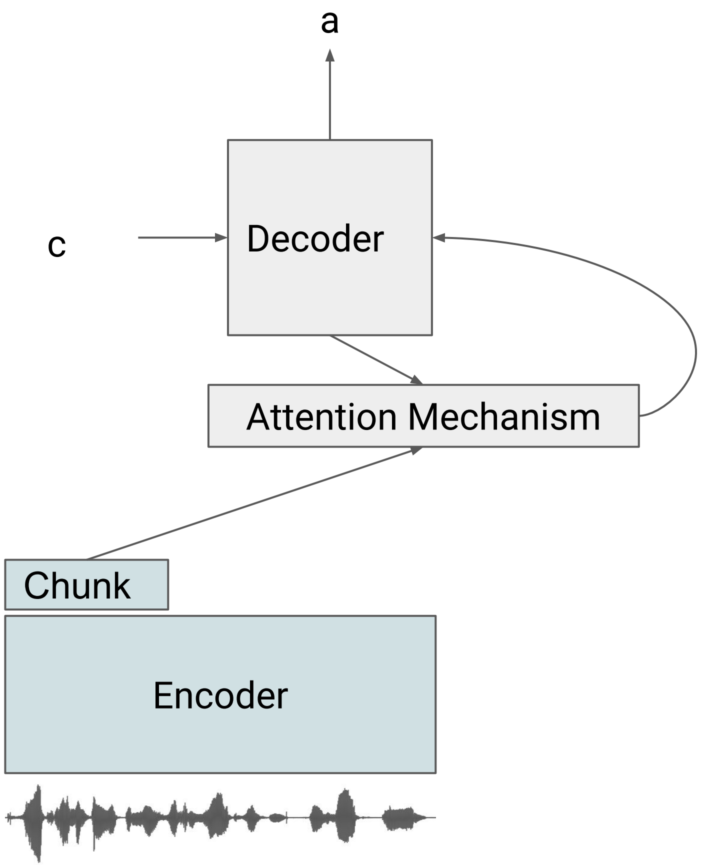
Online Models

- LAS is not streaming
- We will show a thorough comparison of different online models
  - RNN-T [Graves, 2012], [Rao et al., 2017]
  - Neural Transducer [Jaitly et al., 2015], [Sainath et al., 2018]
  - MoChA [Chiu and Raffel, 2018]

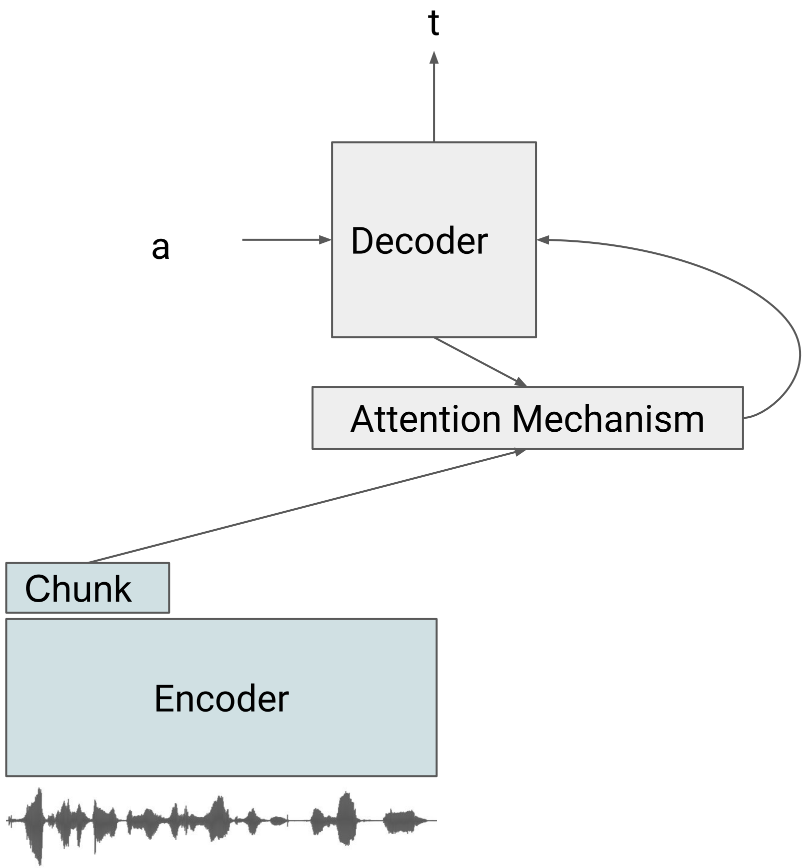
(1) Neural Transducer: “Online” Attention Models



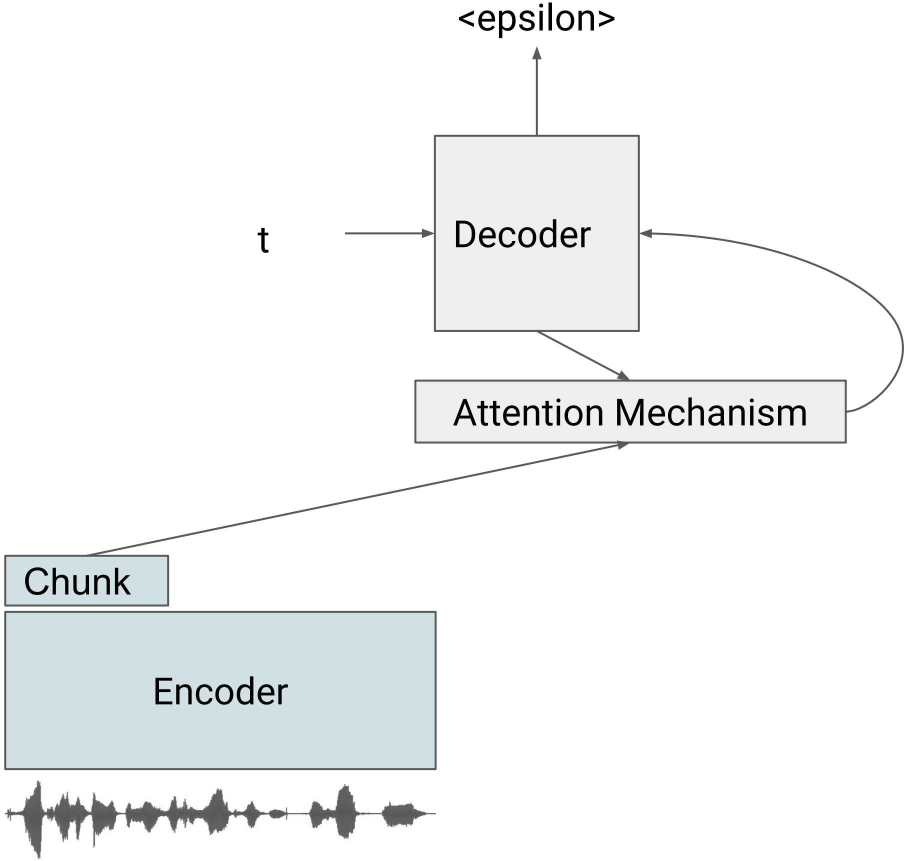
(1) Neural Transducer: "Online" Attention Models



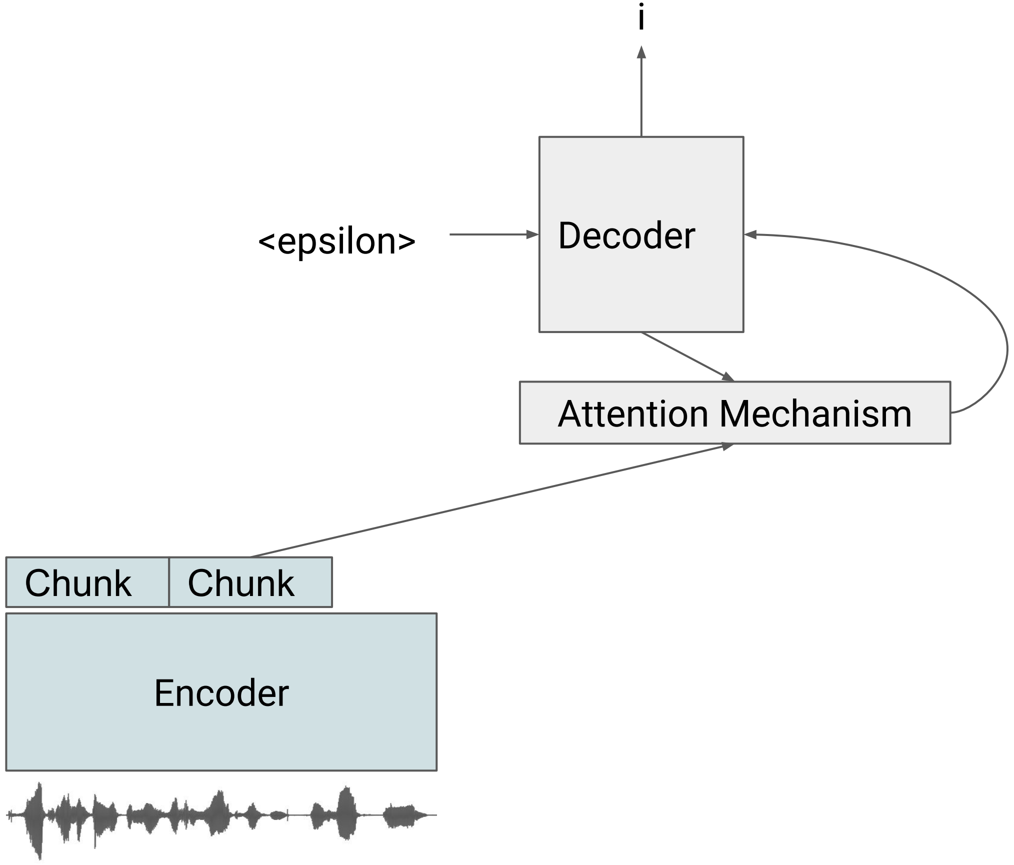
(1) Neural Transducer: “Online” Attention Models



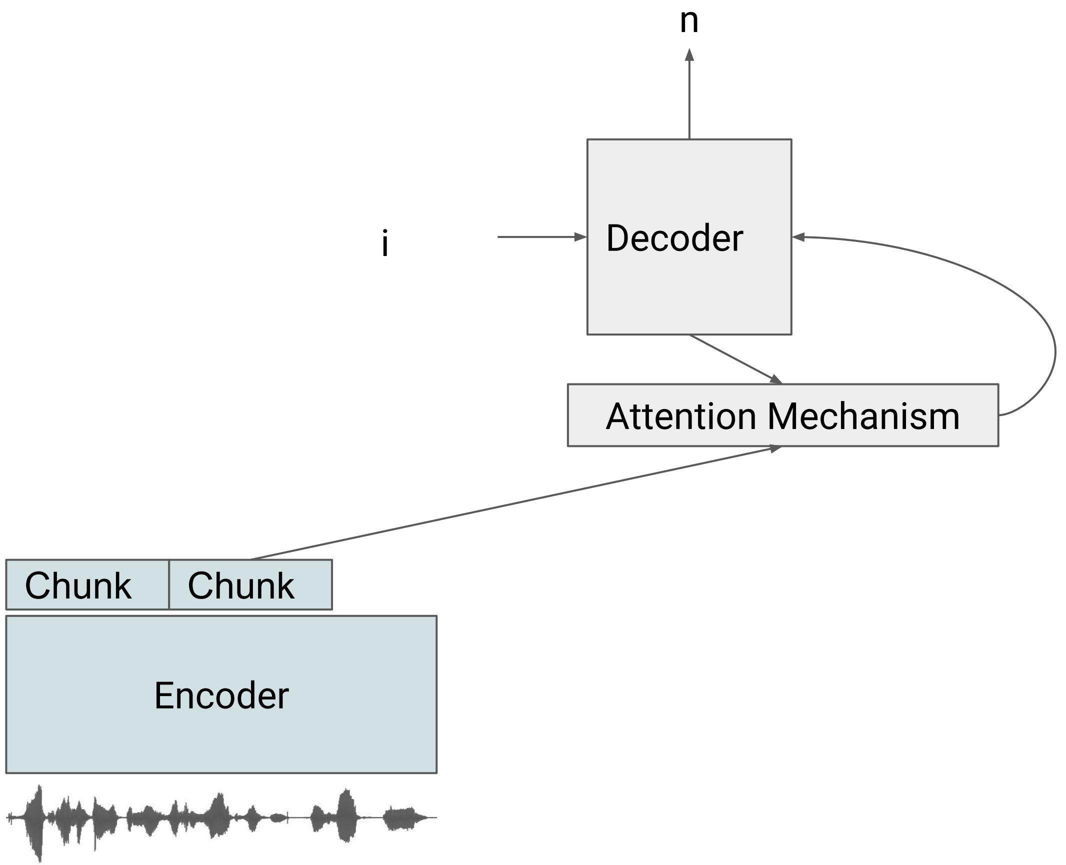
(1) Neural Transducer: “Online” Attention Models



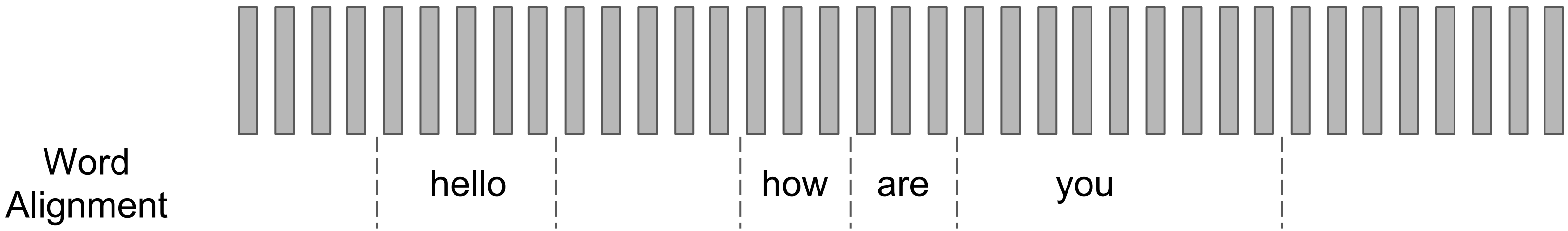
(1) Neural Transducer: “Online” Attention Models



(1) Neural Transducer: “Online” Attention Models

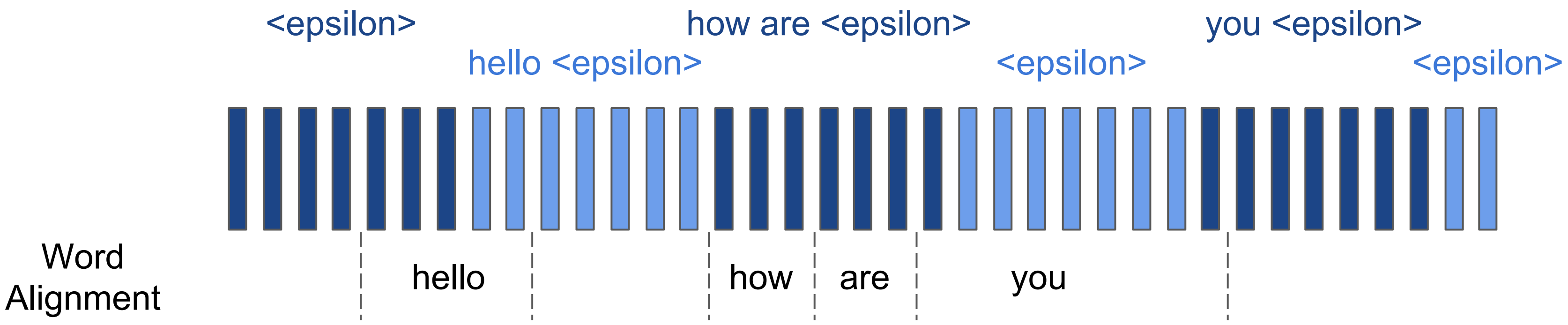


Training Data for Neural Transducer



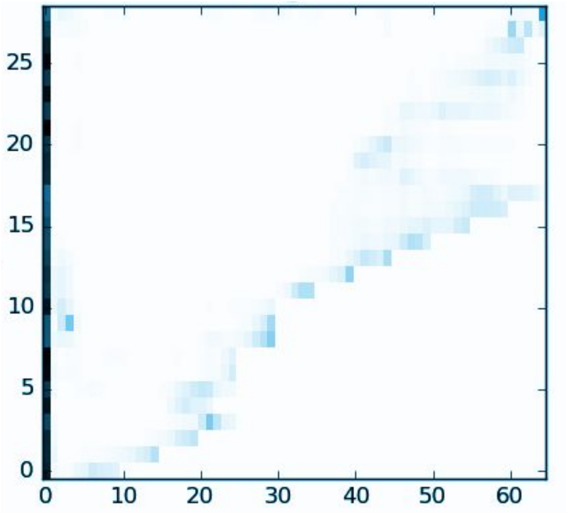
- Online methods like RNN-T, Policy Gradient learn alignment jointly with model
- We train neural transducer with a pre-specified alignment, so don't need to re-compute alignments (e.g., forward-backward) during training, which slows things down on GPU

Training Data for Neural Transducer

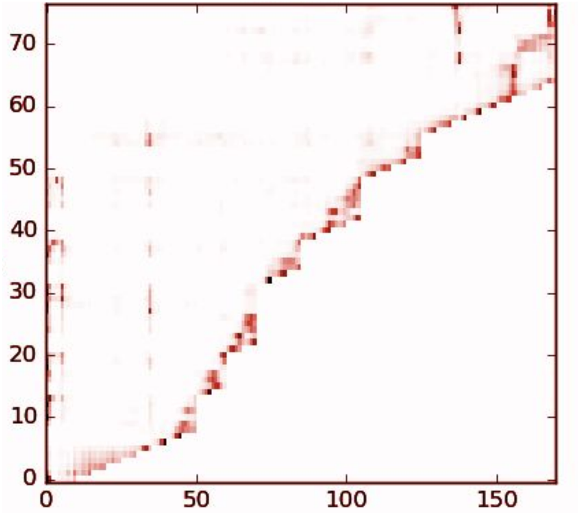


- <epsilon> signals end-of-chunk
- Since we don't have grapheme-level alignments, we wait till the end of the word to emit the entire word's graphemes

Neural Transducer Attention Plot



Unidirectional LAS with
Multi-Headed Attention

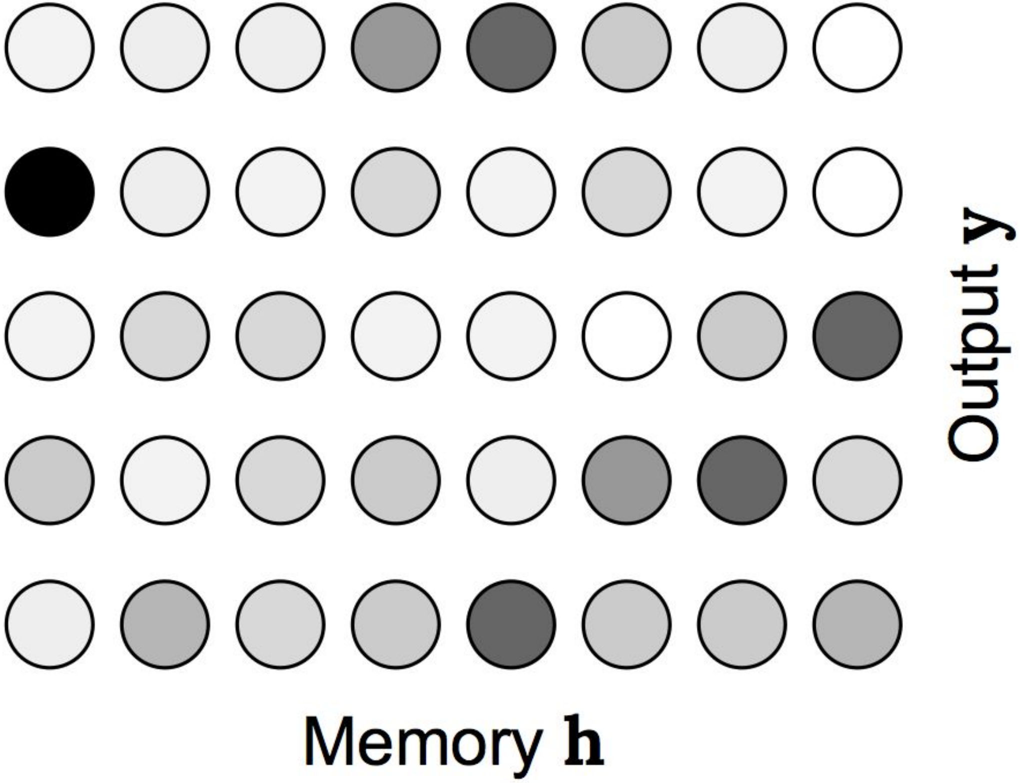


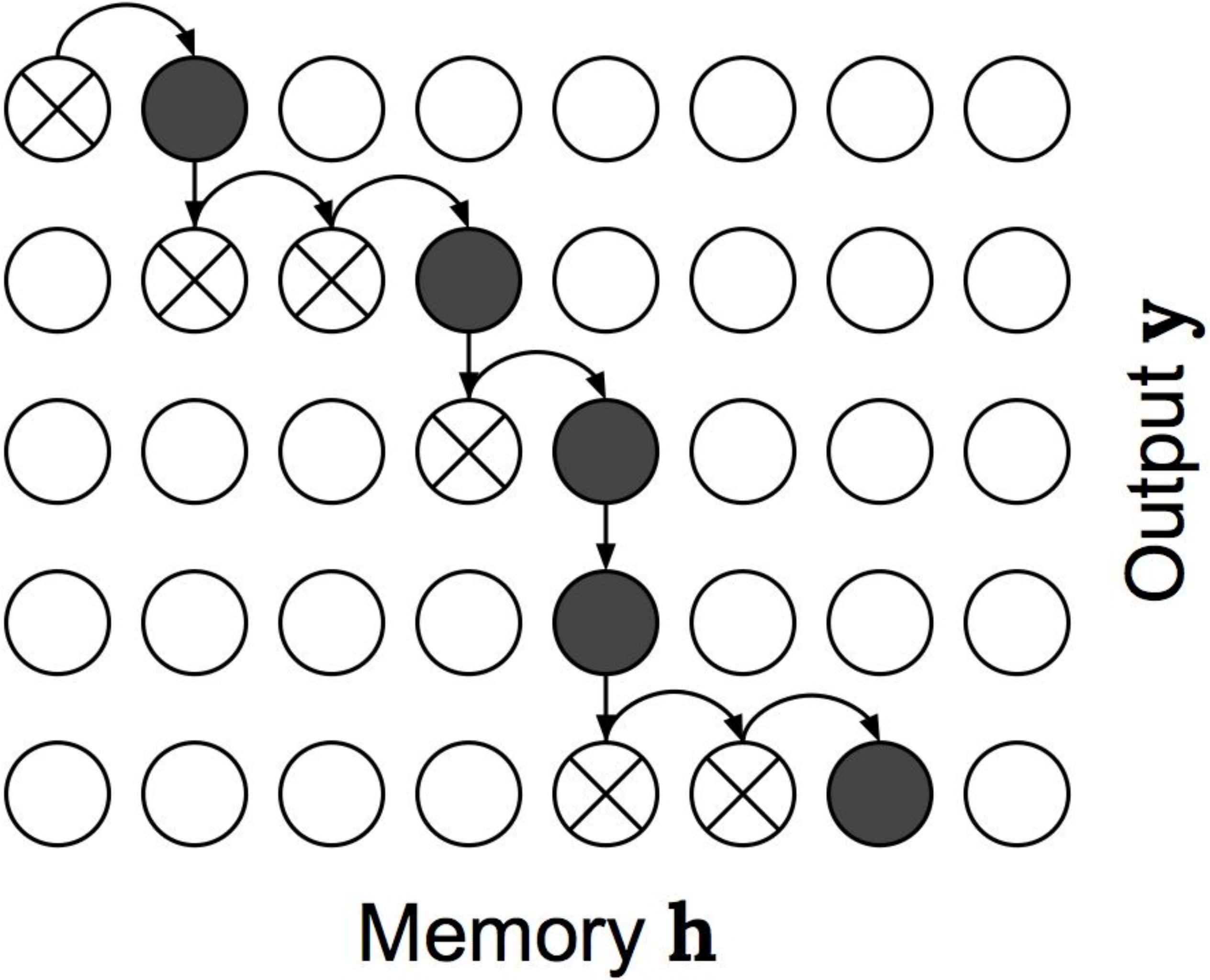
Neural Transducer Attention

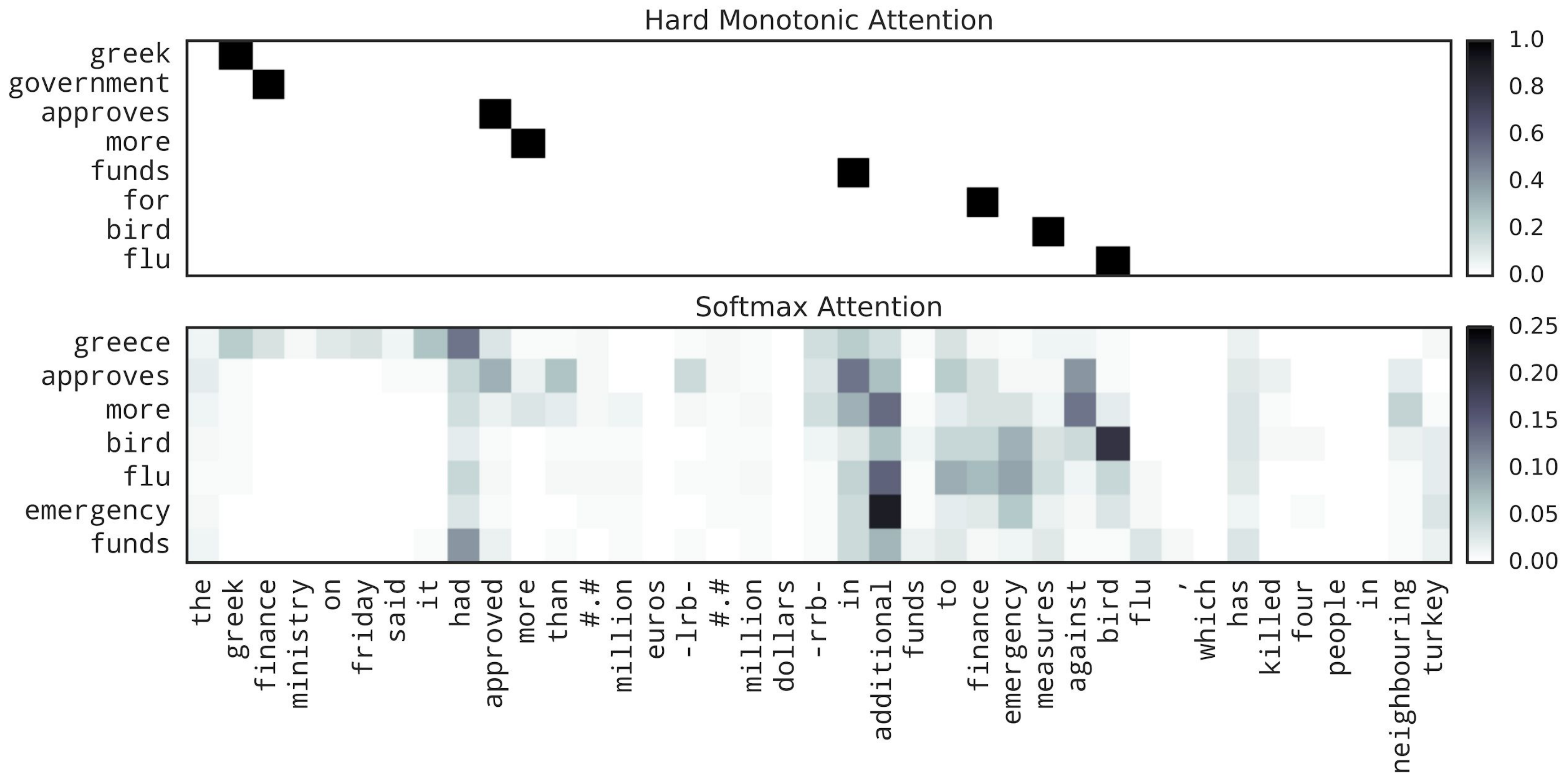
NT model examines previous frames without looking beyond the current chunk

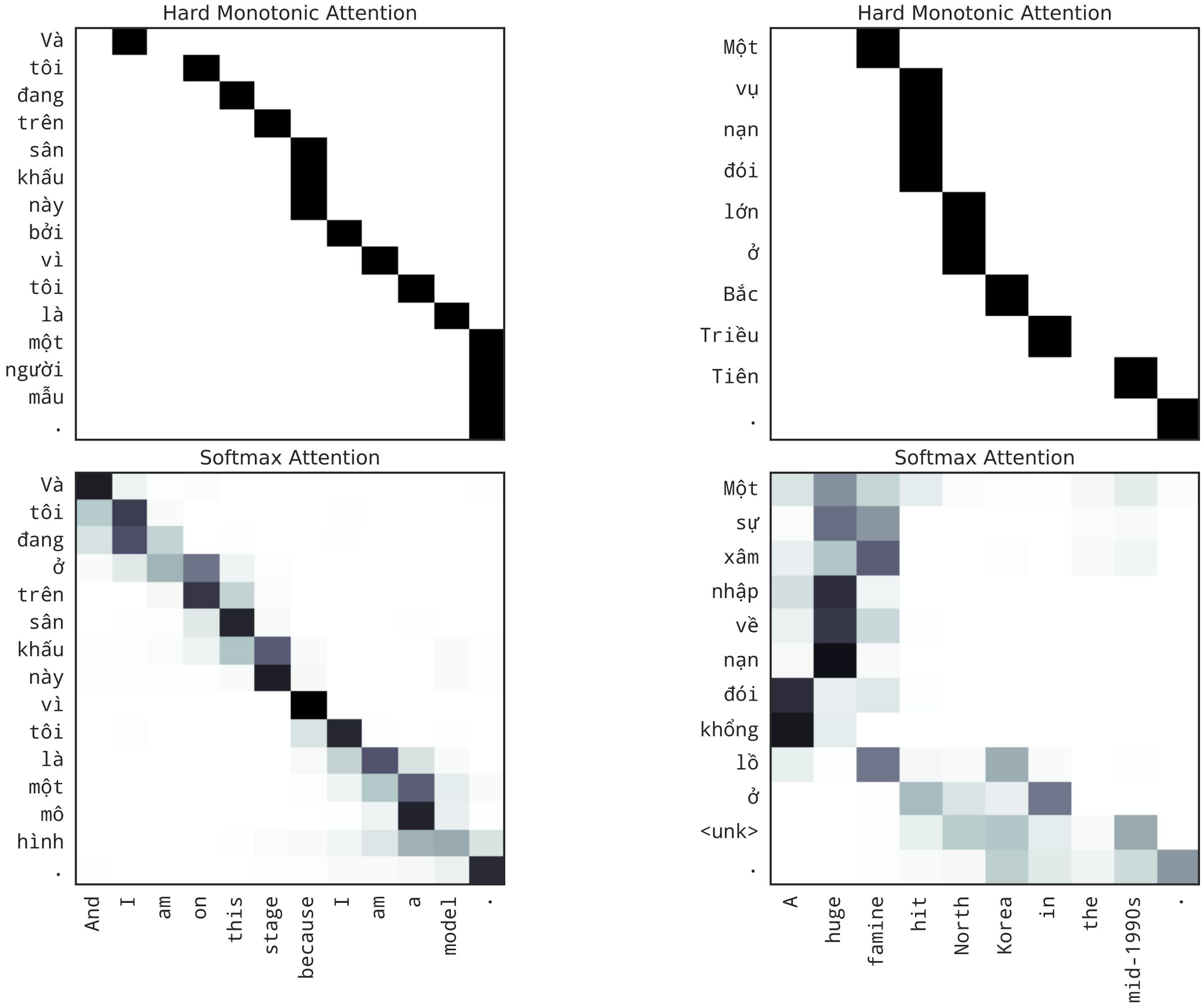
Google

(2) Monotonic Attention



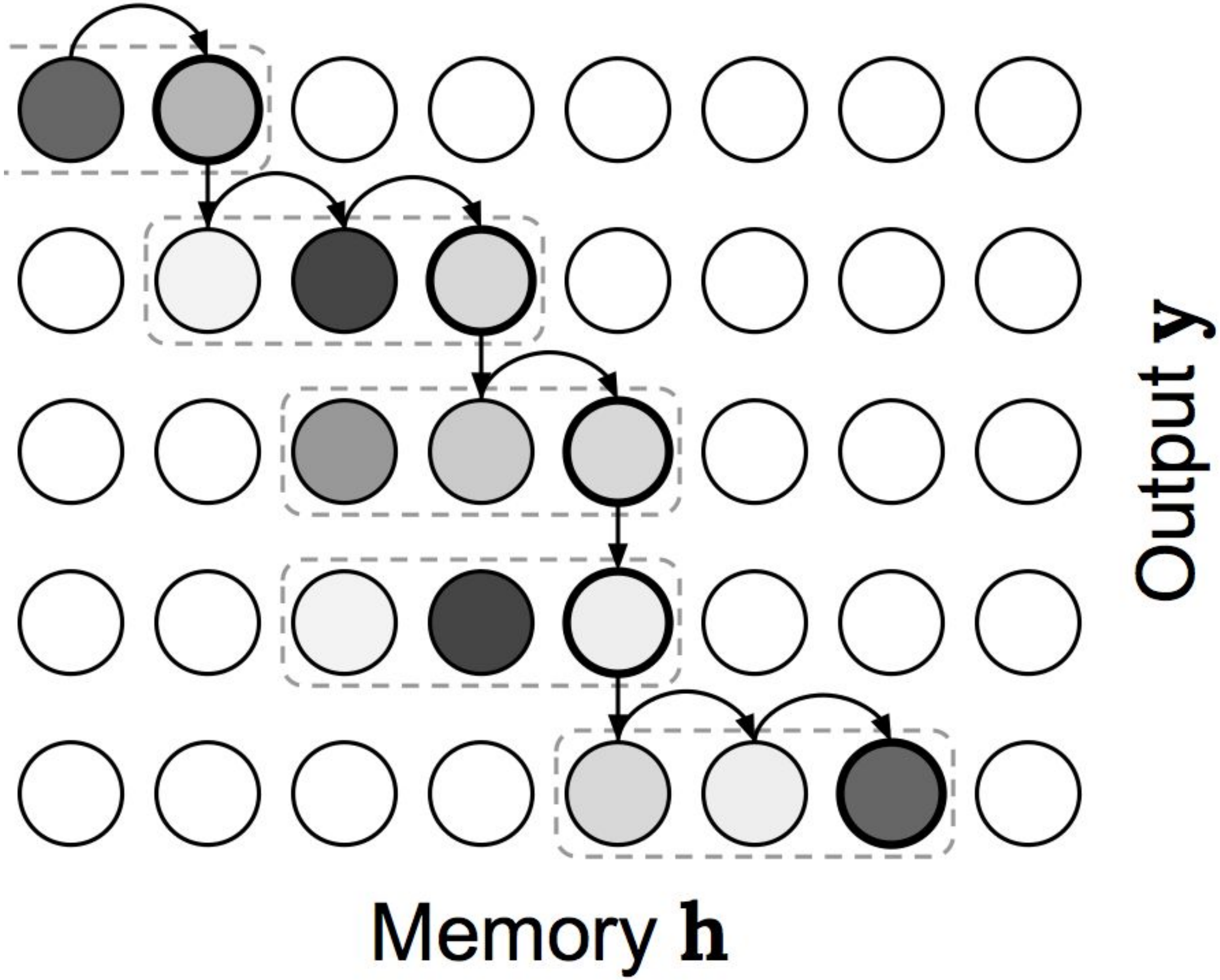

Output $\mathbf{y}$
Memory $\mathbf{h}$

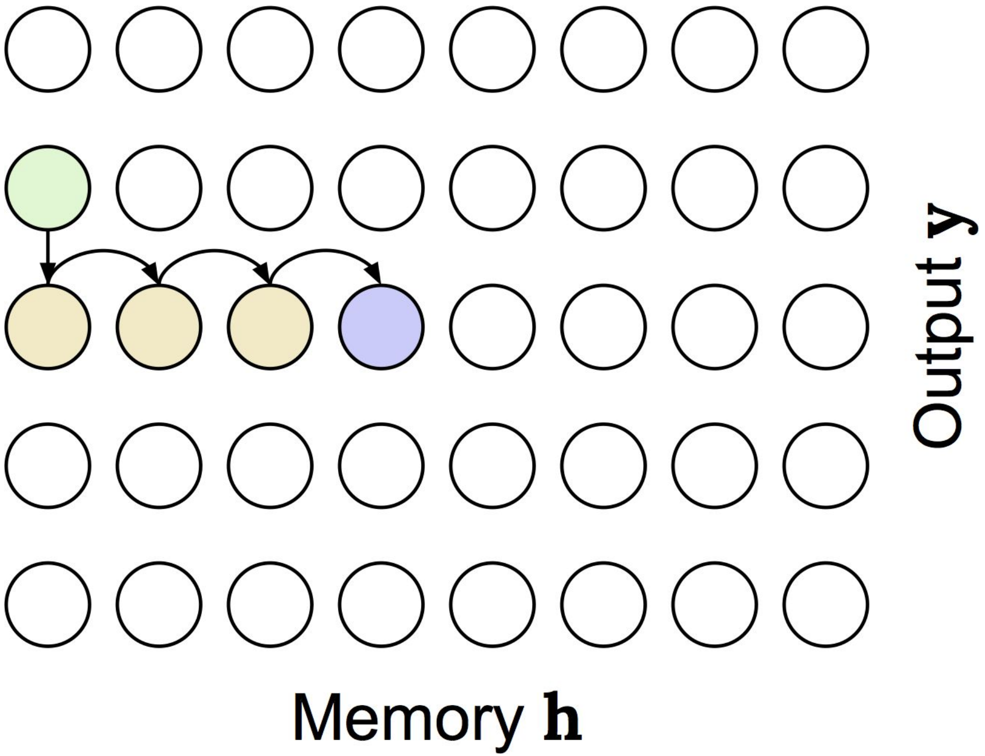

Hard Monotonic Attention
greek
government
approves
more
funds
for
bird
flu
1.0
0.8
0.6
0.4
0.2
0.0
Softmax Attention
greece
approves
more
bird
flu
emergency
funds
0.25
0.20
0.15
0.10
0.05
0.00
the greek finance ministry on friday said it had approved more than #.# million euros -lrb- #.# million dollars -rrb- in additional funds to finance emergency measures against bird flu , which has killed four people in neighbouring turkey



Hard Monotonic Attention
Và tôi đang trên sân khấu này bởi vì tôi là một người mẫu .
Hard Monotonic Attention
Một vụ nạn đói lớn ở Bắc Triều Tiên .
Softmax Attention
Và tôi đang ở trên sân khấu này vì tôi là một mô hình .
And I am on this stage because I am a model .
Softmax Attention
Một sự xâm nhập về nạn đói khổng lồ ở <unk> .
A huge famine hit North Korea in the mid-1990s .

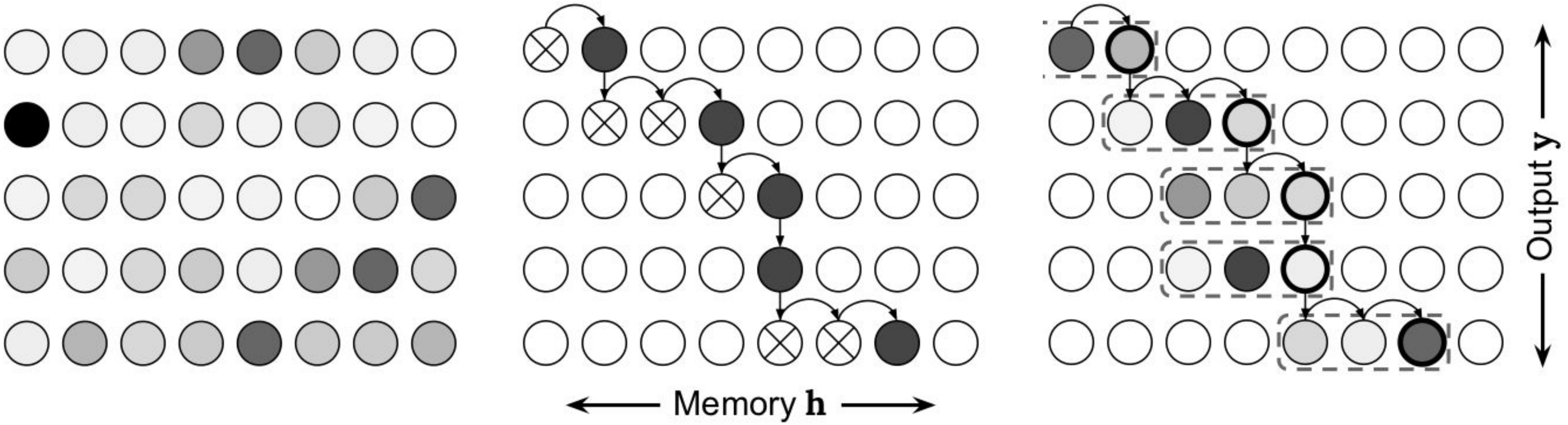
MoChA





$$\text{attention}_{i,j} = \text{select}_{i,j} \sum_{k=1}^{j} \left(\text{attention}_{i-1,k} \prod_{l=k}^{j-1} (1 - \text{select}_{i,l}) \right)$$

(2) Monotonic chunkwise attention (MoChA)



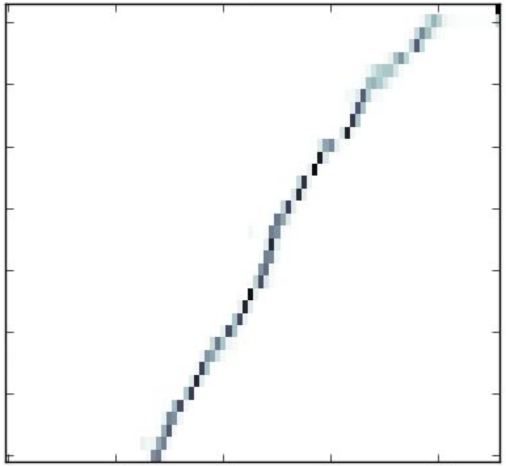
Soft attention Hard monotonic attention Monotonic chunkwise attention

[Chiu and Raffel, 2018]

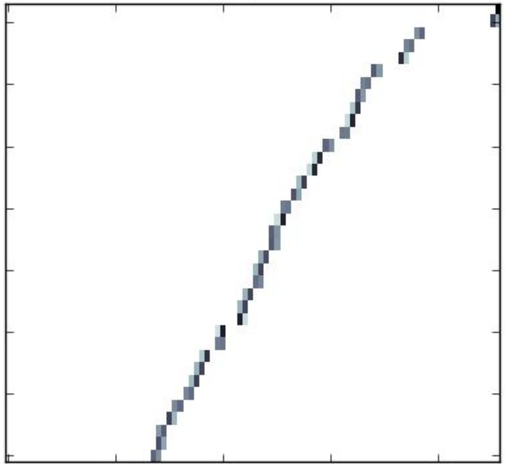
Google

Training monotonic chunkwise attention

- Compute expected probability of hard attention
- The expected probability distribution provides a soft attention
- Same training procedure as LAS



Train



Inference

Online Model Comparison

Model	Clean	
	Voice Search	Dictation
LAS	5.7	4.1
RNN-T	6.8	4.0
MoChA	5.8	4.2
NT	8.7	7.8

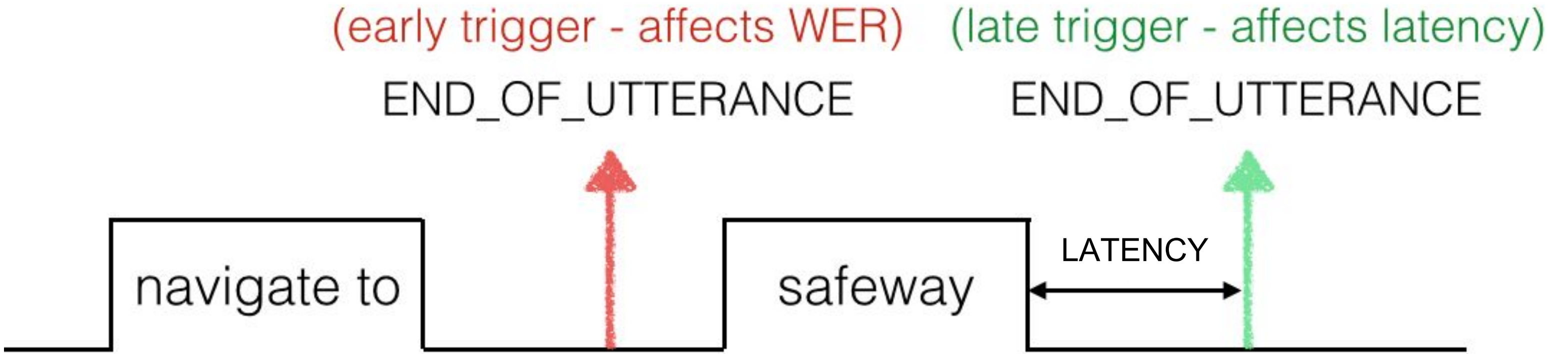
MoChA seems to be a promising online model.

Google

Endpointer

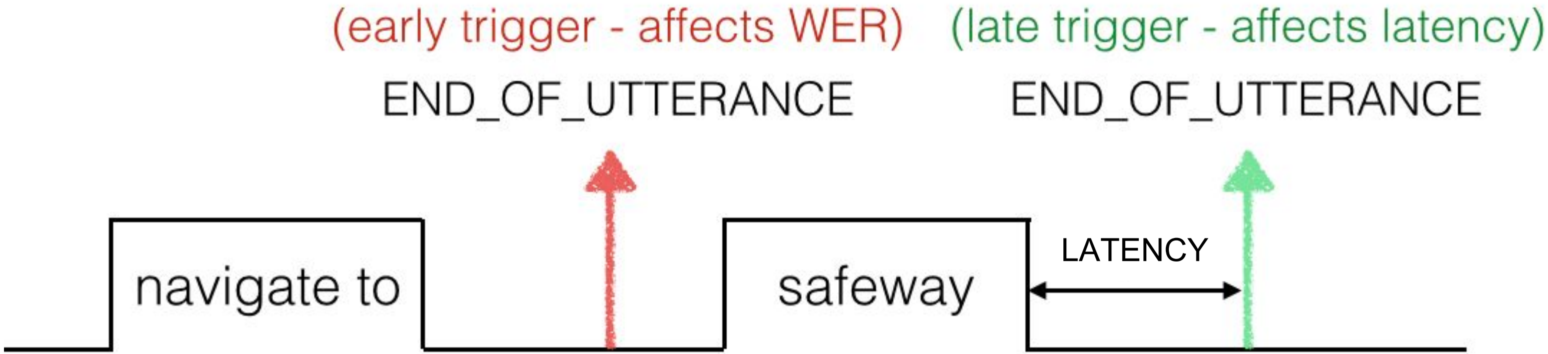
Why is Endpointing hard?

1. Latency vs WER tradeoff

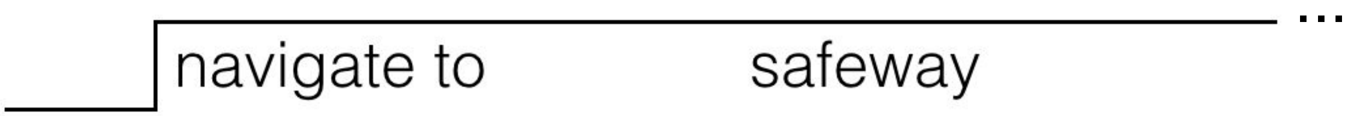


Why is Endpointing hard?

1. Latency vs WER tradeoff

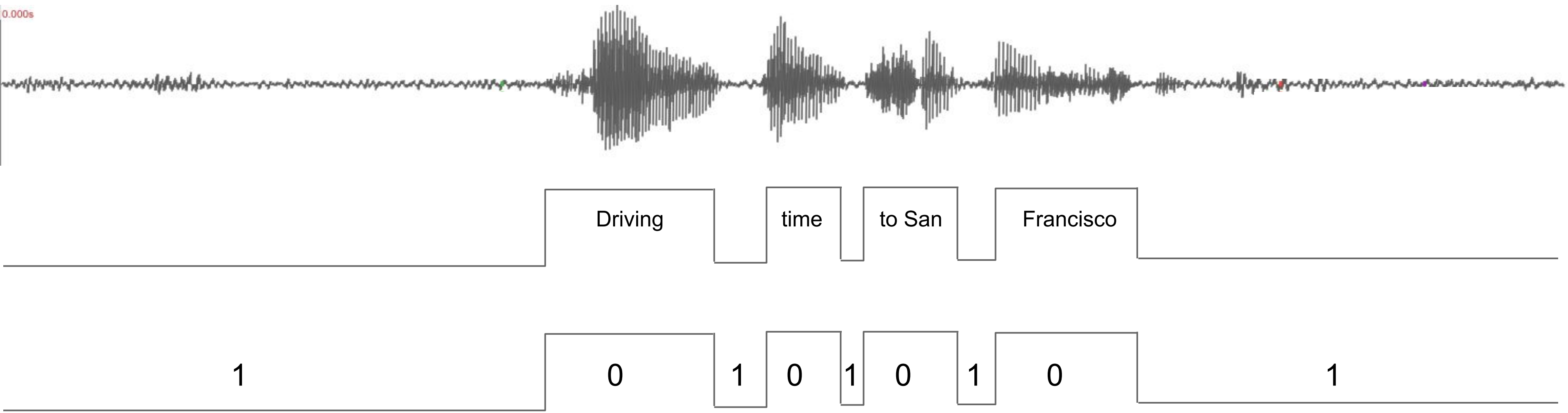


2. Noisy conditions



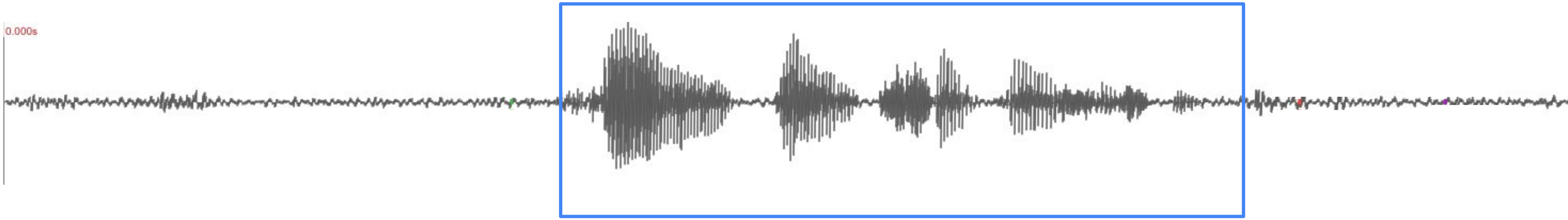
VAD based endpointer

- Use forced alignment to find the timing of the utterance
- Based on the timing mark each frame as SPEECH (0) or NON-SPEECH (1)
- Made mic closing decision when a fixed amount of silence is detected



E2E endpointer

- An unified model does endpointing and ASR
- Add an **<eos>** symbol to the end of each target transcript.
- If top-1 hypothesis in the beam outputs a **<eos>** for a frame **then close mic**.



d r i v e t o sil s a n f r a n c i s c o **<eos>**

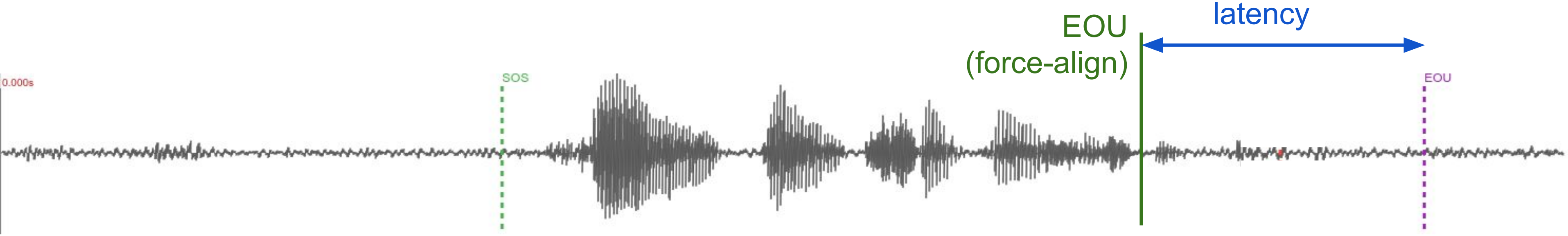
E2E endpointer

Parameters to precise control E2E endpointing:

- Cost penalty: scale up for **<eos>** cost
- Pruning: max cost of **<eos>** allowed in beam search

Similar to thresholds for EOU detector or VAD

Evaluating an Endpointer



- Measure endpointer latency
  - Use forced alignment to find the time of the 'sil' that's not followed by speech.
  - Compare that to the timestamp of the END_OF_UTTERANCE.
- Metrics:
  - median latency
  - 90th percentile latency
  - WER

Results summary

- VAD baseline: 900 ms median latency
- VAD -> E2E endpointer: up to ~700 ms improvement!!

	WER	Median latency	90th percentile latency
(1) CTC AM	14.5	890	960
(2) RNNT no EP	8.4	-	-
(3) RNNT + VAD EP	8.8	900	1030
(4) E2E RNNT EP	8.8	210	1010

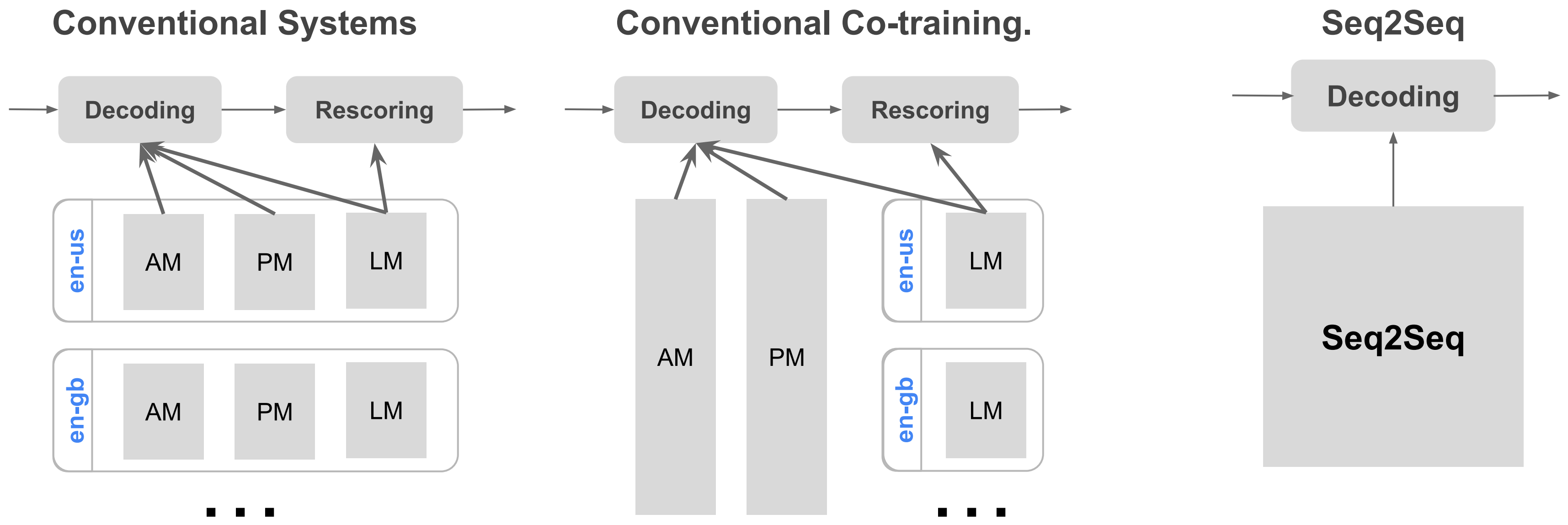
Extensions of E2E Models

Google

Multi-Dialect Speech Recognition With A Single Seq2Seq Model

[Li et al., 2018]
[Toshniwal et al., 2018]

Multi-Dialect ASR



In conventional systems, languages/dialects, are handled with **individual AMs, PMs and LMs**. Upscaling is becoming challenging.

A single model for all.

Multi-Dialect LAS

- Modeling Simplicity
- Data Sharing
  - among dialects and model components
- Joint Optimization
- Infrastructure Simplification
  - a single model for all

Table: Resources required for building each system.

Conventional	**Seq2Seq**
data phoneme lexicon text normalization LM × N	data

Motivations

- We share the same interest:
  - *S. Watanabe, T. Hori, J.R. Hershey*; **Language independent end-to-end architecture for joint language identification and speech recognition**; ASRU 2017. MERL, USA.
    - English, Japanese, Mandarin, German, Spanish, French, Italian, Dutch, Portuguese, Russian.
  - *S. Kim, M.L. Seltzer*; **Towards language-universal end-to-end speech recognition**; submitted to ICASSP 2018. Microsoft, USA.
    - English, German, Spanish.

Google

Multi-Dialect LAS

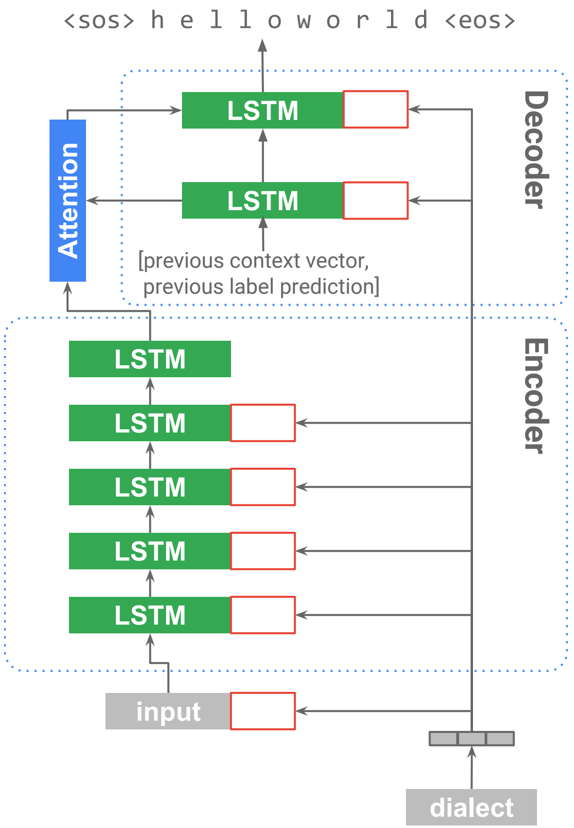
Dialect as Output Targets

- Multi-Task Learning: Joint Language ID (LID) and ASR
  - LID first, then ASR
    - "<sos> **<en-gb>** h e l l o ⊔ w o r l d <eos>"
    - LID errors may affect ASR performance
  - ASR first, then LID
    - "<sos> h e l l o ⊔ w o r l d **<en-gb>** <eos>"
    - ASR prediction is not dependent on LID prediction, not suffering from LID errors

Dialect as Input Features

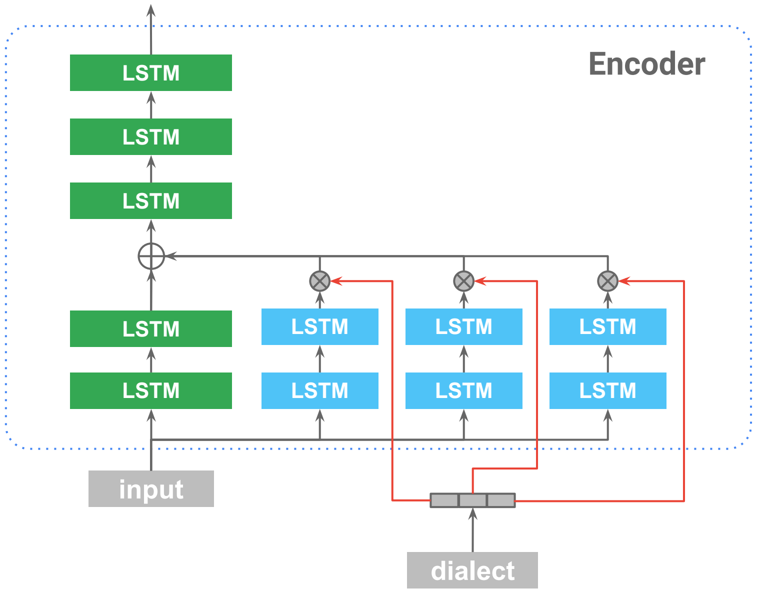
- Passing the dialect information as additional features

components		variations
encoders	→	acoustic
decoders	→	lexicon and language



Dialect Information as Cluster Coefficients

- Cluster Adaptive Training (CAT) [1] coefficients
  - more flexible model architectures
  - larger capacity in variation modeling
  - but increased model parameters

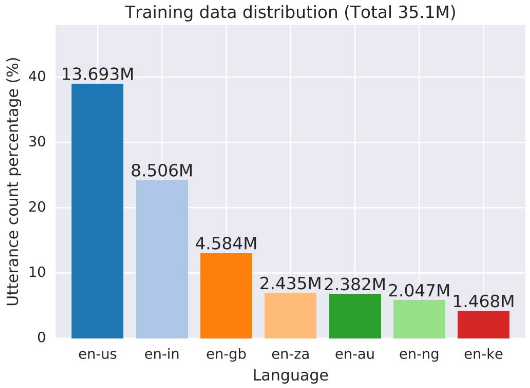


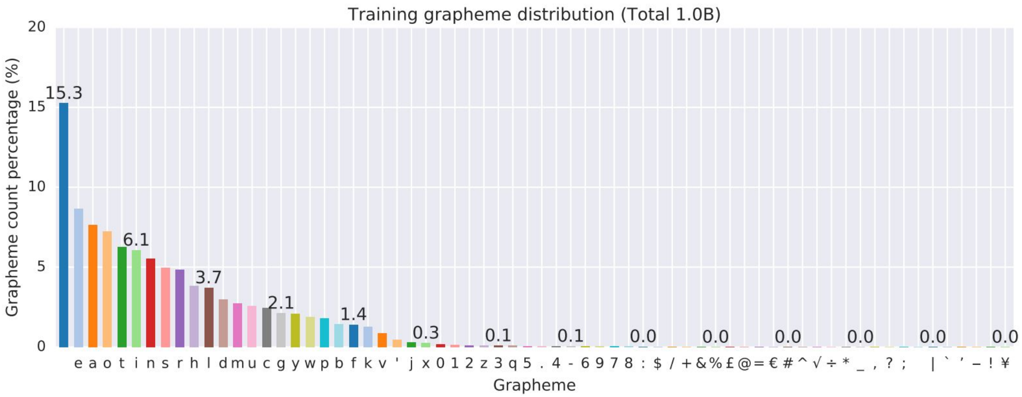
[1] Tian Tan, Yanmin Qian and Kai Yu, "Cluster adaptive training for deep neural network based acoustic model", IEEE/ACM TASLP, 2016

Experimental Evaluations

Task

- **7 English dialects:** `US (America), IN (India), GB (Britain), ZA (South Africa), AU (Australia), NG (Nigeria & Ghana), KE (Kenya)`





★ unbalanced dialect data

★ unbalanced target classes

LAS Co-training Baselines

Dialect	US	IN	GB	ZA	AU	NG	KE
dialect-ind.	10.6	18.3	12.9	12.7	12.8	33.4	19.2
dialect-dep.	**9.7**	**16.2**	**12.7**	**11.0**	**12.1**	33.4	**19.0**

★ dialect specific **fine-tuning still wins**

★ simply pooling the data is **missing** certain dialect specific variations

LAS With Dialect as Output Targets

Dialect	US	IN	GB	ZA	AU	NG	KE
Baseline (dialect-dep.)	9.7	**16.2**	12.7	11.0	12.1	33.4	19.0
LID first	9.9	16.6	12.3	11.6	12.2	33.6	18.7
ASR first	**9.4**	16.5	**11.6**	**11.0**	**11.9**	**32.0**	**17.9**

- ★ LID error **affects** ASR
- ★ **ASR first** is better

	Example target sequence
LID first	`<sos> <en-gb> h e l l o ⊔ w o r l d <eos>`
ASR first	`<sos> h e l l o ⊔ w o r l d <en-gb> <eos>`

LAS With Dialect as Input Features

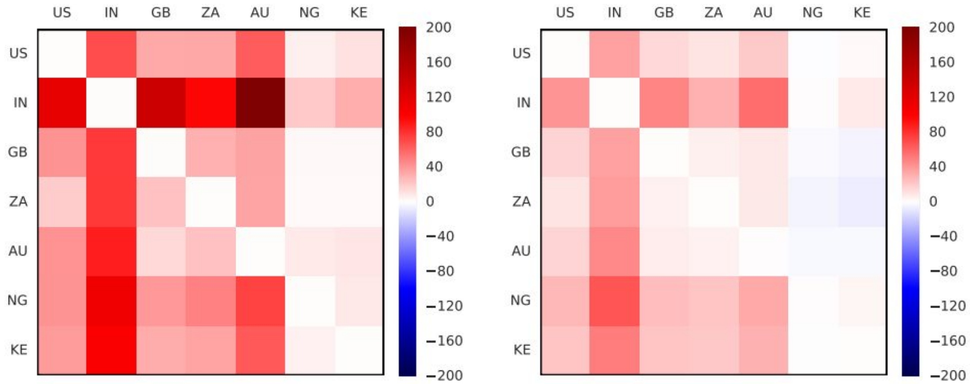
Dialect		US	IN	GB	ZA	AU	NG	KE
Baseline (dialect-dep.)		9.7	16.2	12.7	11.0	12.1	33.4	19.0
encoder	**1-hot**	9.6	16.4	11.8	10.6	10.7	31.6	18.1
	emb.	9.6	16.7	12.0	10.6	10.8	32.5	18.5
decoder	**1-hot**	9.4	16.2	11.3	10.8	10.9	32.8	18.0
	emb.	9.4	16.2	**11.2**	10.6	11.1	32.9	18.0
both	**1-hot**	**9.1**	**15.7**	11.5	**10.0**	**10.1**	**31.3**	**17.4**

★ dialect 1-hot and embedding (emb.) performs **similarly**

★ feeding dialect to **both encoder and decoder** gives the largest gains

LAS With Dialect as Input Features

Figure: Feeding different dialect vectors (rows) to the LAS encoder and decoder on different test sets (columns).



(a) Encoder (b) Decoder

★ **encoder** is more sensitive to wrong dialects → large acoustic variations

★ for **low-resource** dialects (NG, KE), the model **learns to ignore** the dialect information

Google

LAS With Dialect as Input Features

- The dialect vector does **both AM and LM adaptation**

*Table: The number of **color**/**colour** occurrences in hypotheses on the **en-gb** test data.*

dialect vector	encoder	decoder	color (US)	colour (GB)
×	×	×	1	22
<en-gb>: [0, 1, 0, 0, 0, 0, 0]	✓	×	19	4
<en-gb>: [0, 1, 0, 0, 0, 0, 0]	×	✓	0	25
<en-us>: [1, 0, 0, 0, 0, 0, 0]	×	✓	24	0

★ dialect vector helps **encoder** to **normalize accent variations**

★ dialect vector helps **decoder** to **learn dialect-specific lexicons**

LAS With Dialect as CAT coefficients

Dialect		US	IN	GB	ZA	AU	NG	KE
Baseline (dialect-dep.)		9.7	16.2	12.7	11.0	12.1	33.4	19.0
input features (encoder)	**1-hot**	9.6	16.4	11.8	10.6	10.7	**31.6**	**18.1**
CAT coeff.	**1-hot**	9.9	17.0	12.1	11.0	11.6	32.5	18.3
	emb.	**9.4**	**16.1**	**11.7**	**10.6**	**10.6**	32.9	**18.1**

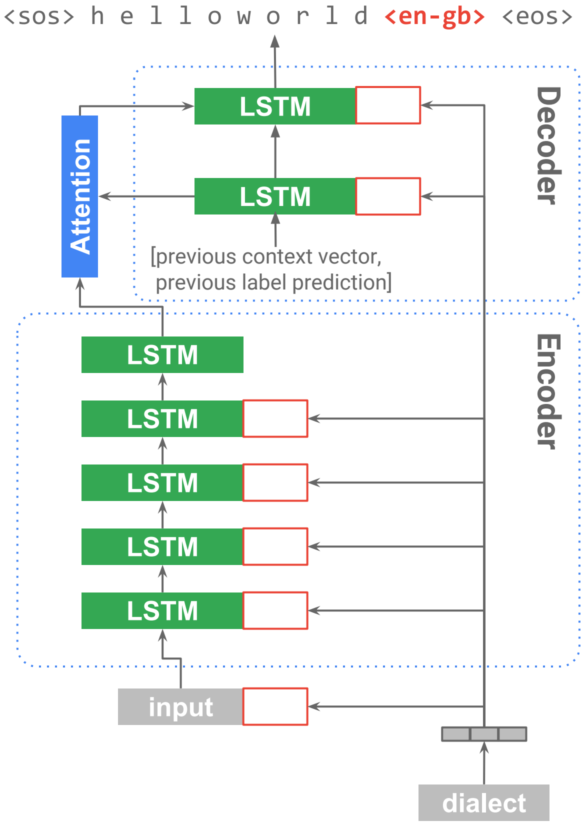
★ dialect as CAT coefficients is much better than as inputs

★ but with large model params increase (160K vs. 3M)

Final Multi-Dialect LAS

Final Multi-Dialect LAS

- output targets:
  - multi-task with ASR first
- input features:
  - feeding dialect to both encoder and decoder



Google

Final Multi-Dialect LAS

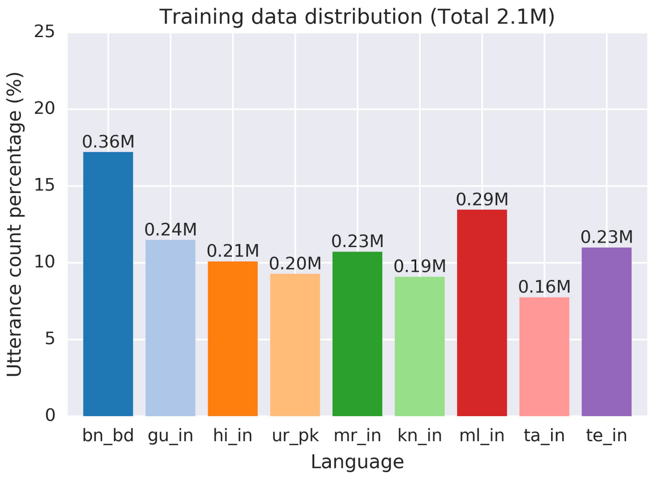
Dialect	US	IN	GB	ZA	AU	NG	KE
Baseline (dialect-dep.)	9.7	16.2	12.7	11.0	12.1	33.4	19.0
output targets (ASR first)	9.4	16.5	11.6	11.0	11.9	32.0	17.9
input features (both)	**9.1**	**15.7**	11.5	10.0	**10.1**	**31.3**	**17.4**
final	**9.1**	16.0	**11.4**	**9.9**	10.3	31.4	17.5

★ **small gains** when combining input and output

★ the final system **outperforms** the dialect-dependent models by 3.1~16.5% relatively

IndicX - Task

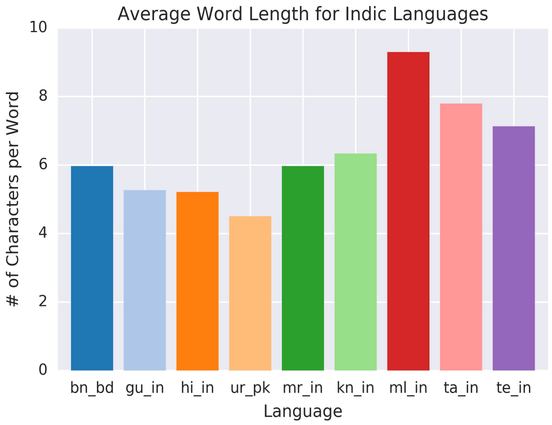
- **9 Indian languages:** bn_bd, gu_in, hi_in, ur_pk, mr_in, kn_in, ml_in, ta_in, te_in
- **large script variations**

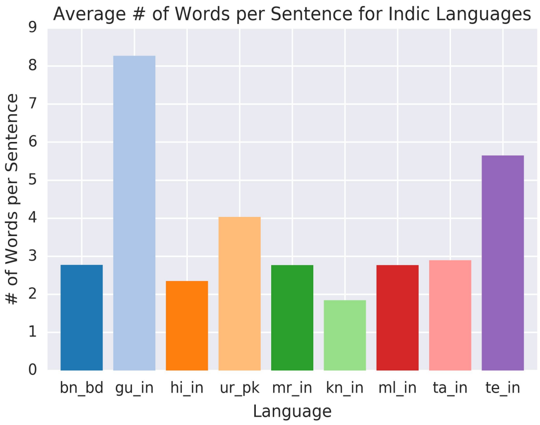


- Bengali (bn_bd) - আমার বাবা ওদেরকে বলতেন
- Gujarati (gu_in) - હું ઘરની અંદર ન મરું અને બહાર પણ ન મરું
- Hindi (hi_in) - पहले वीडियोग्राफी होगी
- Kannada (kn_in) - ಮುಖದ ಮಧ್ಯದಲ್ಲಿ ಪಿಷ್
- Malayalam (ml_in) - എന്നിട്ടും അവരുടെ വാക്കുകളിലൂടെ അവരെ
- Marathi (mr_in) - श्रीकृष्णाच्या गोकुळातल्या
- Tamil (ta_in) - இது ஒரு நகராட்சியாகும்
- Telugu (te_in) - ఈ పేజీని 'తరుజ్మా' చేయకముందు ఇవికీలో పెడదామా
- Urdu (ur_pk) - شیخ عبدالرحیم گرھوڑی جو کلاہ مصنف

[1] S. Toshniwal, T.N. Sainath, R.J. Weiss, B. Li et.al Multilingual speech recognition with a single end-to-end model, *ICASSP 2018*

IndicX - Task

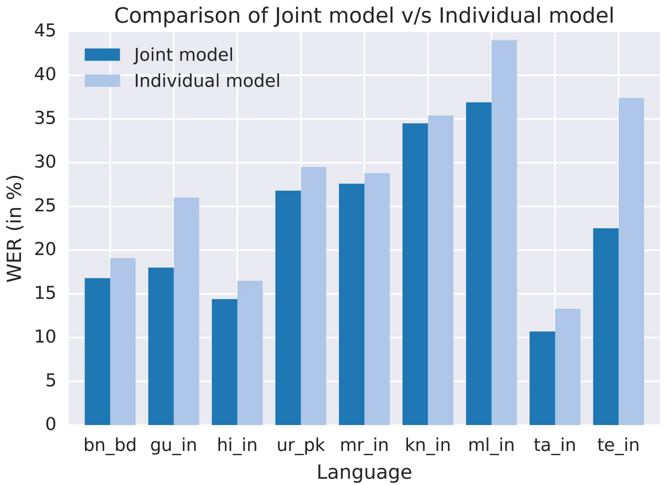


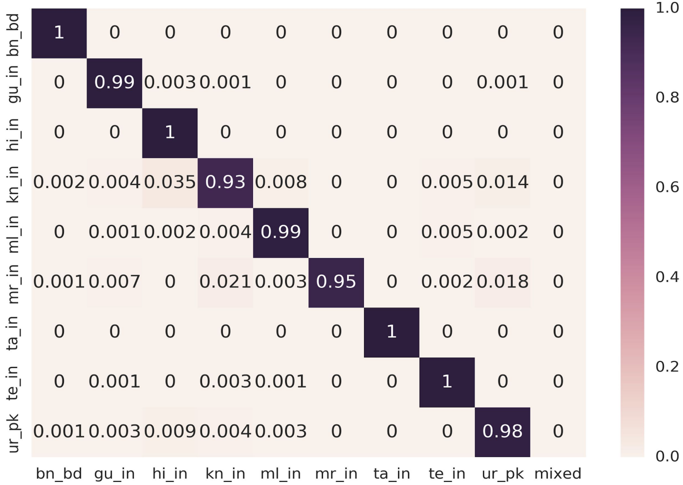


- ★ **large variations in graphemes**
- ★ **totally 964 unique graphemes**
- ★ **lexicon variations**
- ★ **LM variations**

Google [1] S. Toshniwal, T.N. Sainath, R.J. Weiss, B. Li et.al Multilingual speech recognition with a single end-to-end model, *ICASSP 2018*

IndicX - Co-training





★ **co-trained model is consistently better**

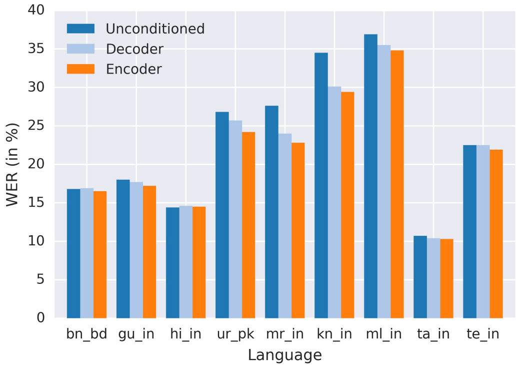
★ **co-trained model chooses the right script**

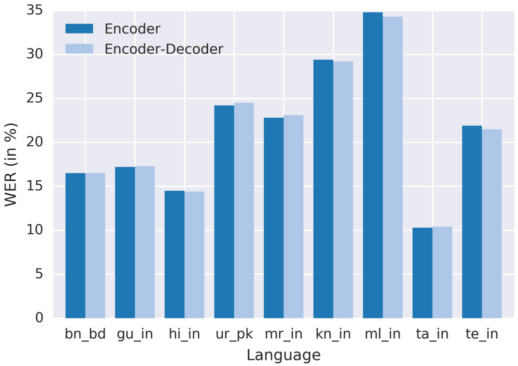
★ **tested multitask learning (LID and ASR), not helpful**

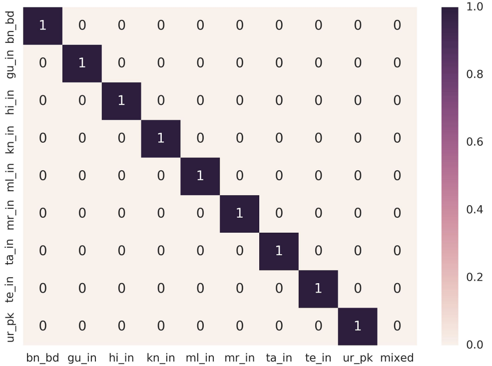
★ **the model cannot do code switching, faithful to one language**

Google [1] S. Toshniwal, T.N. Sainath, R.J. Weiss, B. Li et.al [Multilingual speech recognition with a single end-to-end model](), *ICASSP 2018*

IndicX - Co-training with LID







★ helps more on encoder

★ feeds to encoder only is sufficient

★ chooses the correct script

★ faithful to language ID, wrong ID leads to wrong script

[1] S. Toshniwal, T.N. Sainath, R.J. Weiss, B. Li et.al [Multilingual speech recognition with a single end-to-end model](), *ICASSP 2018*

Summary and Open questions

- Summary
  - End-to-end models can be competitive to production
  - We now have models which can endpoint, are streaming, can do contextual biasing
- Open Questions
  - How to inject pronunciations?
  - How to handle long-tail problems (numerics)?
- Expanding to new domains
  - Speech To Parse
  - Audio-visual

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