CS 224S / LINGUIST 285
Spoken Language Processing

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Spring 2017

Lecture 8: End-to-end neural network speech recognition

Outline

- ASR discussion thus far
- Connectionist temporal classification (CTC)
- Lexicon-free CTC
- Scaling up end-to-end neural approaches
- Alternative end-to-end approaches
- HW3 discussion

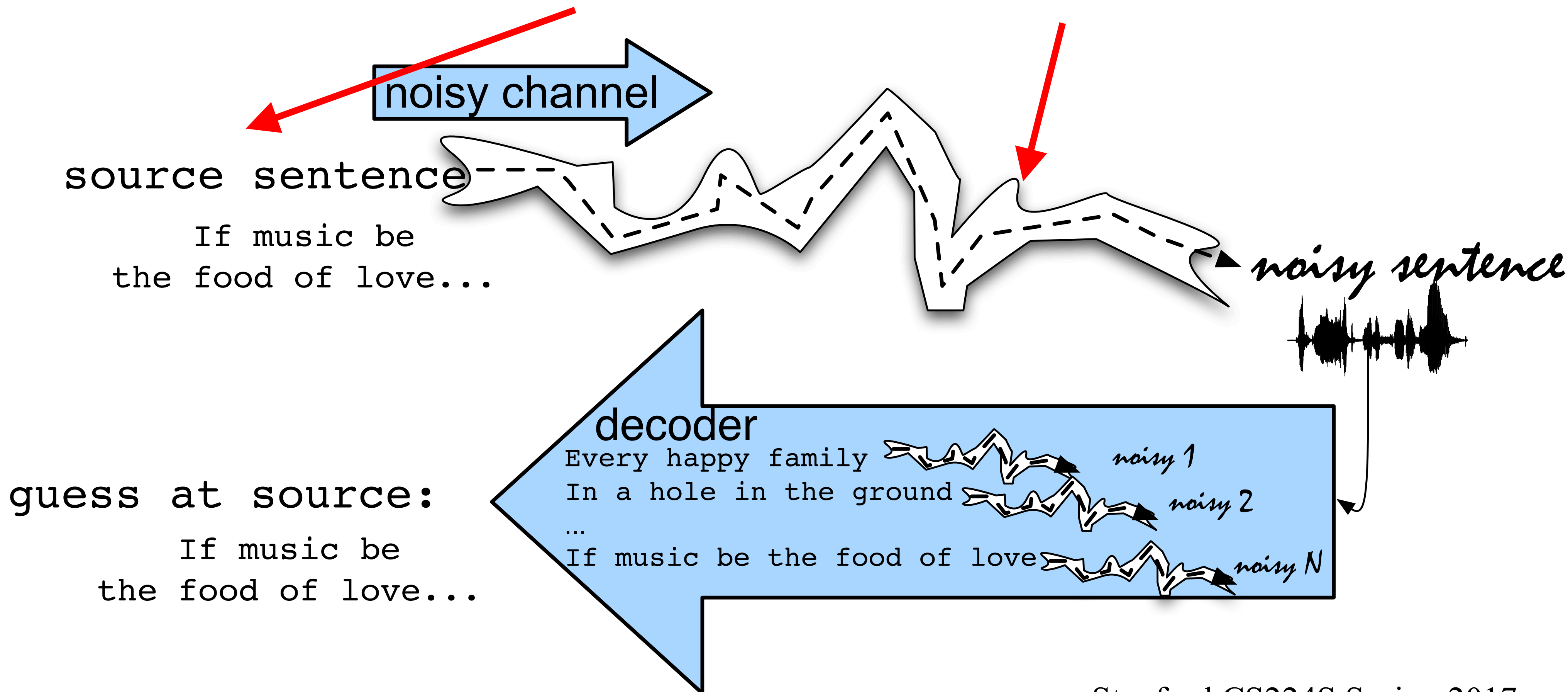
Noisy channel model

likelihood prior

$$\hat{W} = \underset{W \in L}{\arg\max}\, P(O \mid W)\, P(W)$$

The noisy channel model

Ignoring the denominator leaves us with two factors: P(Source) and P(Signal|Source)

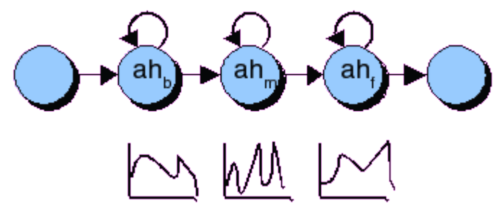


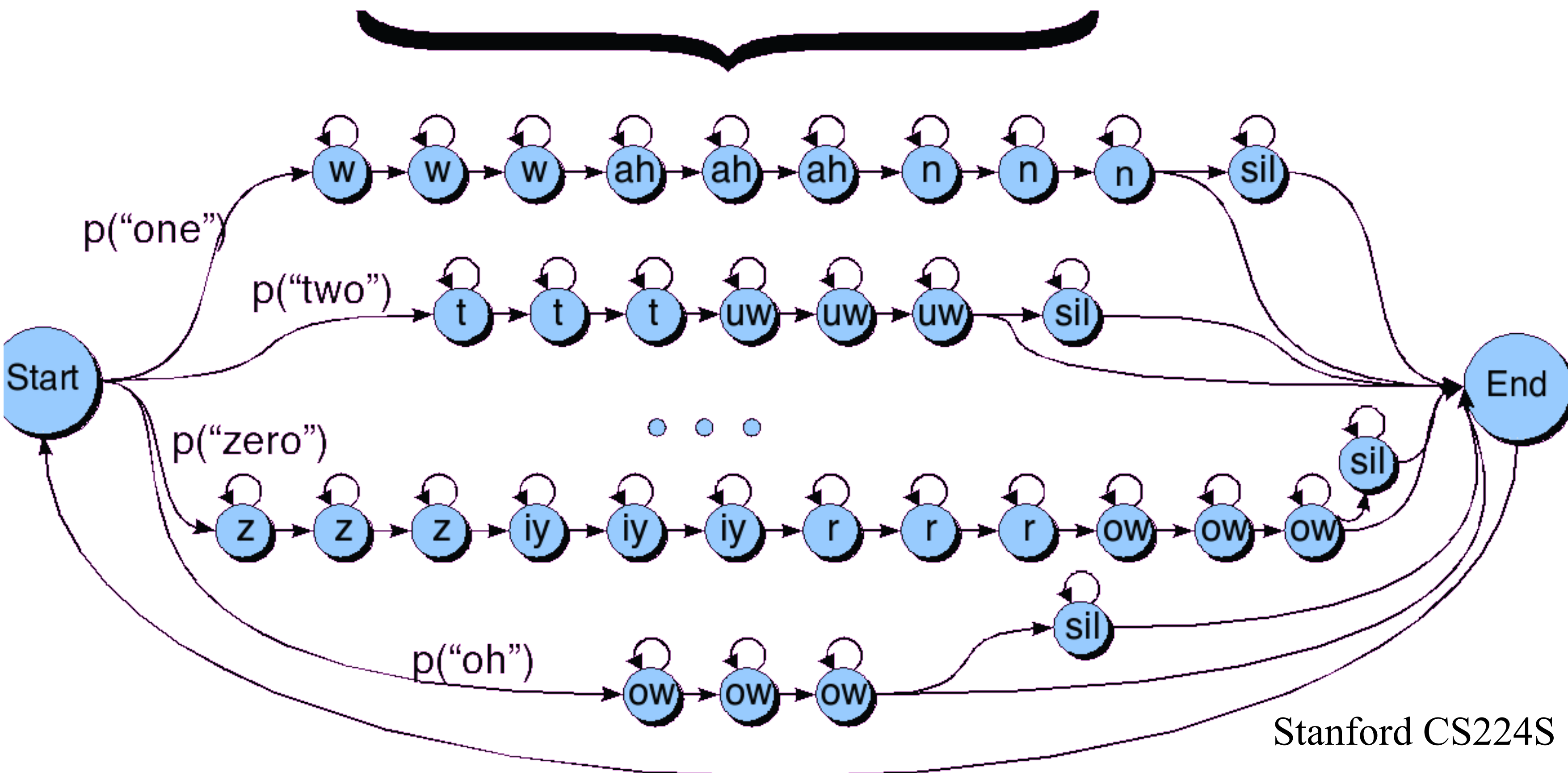
HMM for the digit recognition task

Lexicon

one	w ah n
two	t uw
three	th r iy
four	f ao r
five	f ay v
six	s ih k s
seven	s eh v ax n
eight	ey t
nine	n ay n
zero	z iy r ow
oh	ow

Phone HMM





Acoustic Modeling with GMMs

Transcription: Samson

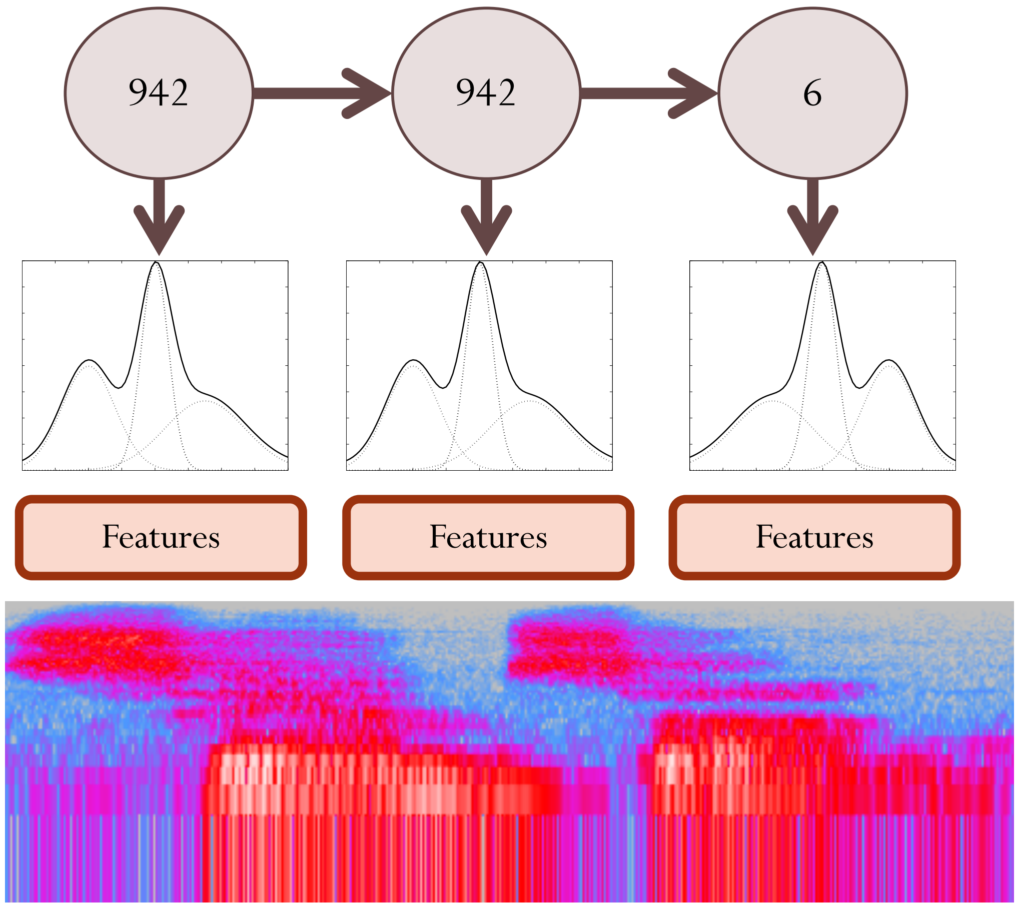
Pronunciation: S – AE – M – S –AH – N

Sub-phones : 942 – 6 – 37 – 8006 – 4422 …

Hidden Markov Model (HMM):

Acoustic Model:

Audio Input:



GMM models:
P(x|s)
x: input features
s: HMM state

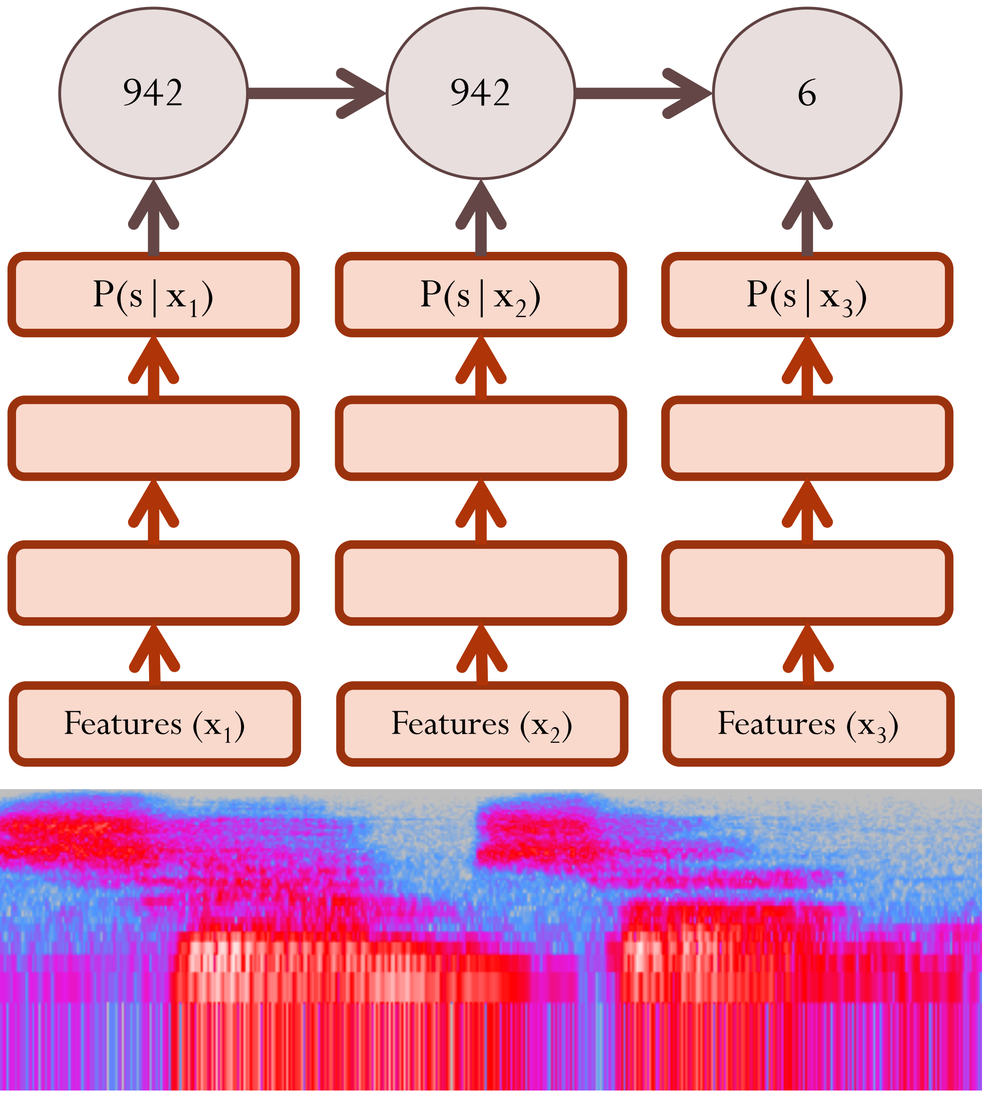
DNN Hybrid Acoustic Models

Transcription: Samson
Pronunciation: S – AE – M – S –AH – N
Sub-phones : 942 – 6 – 37 – 8006 – 4422 …

Hidden Markov Model (HMM):

Acoustic Model:

Audio Input:

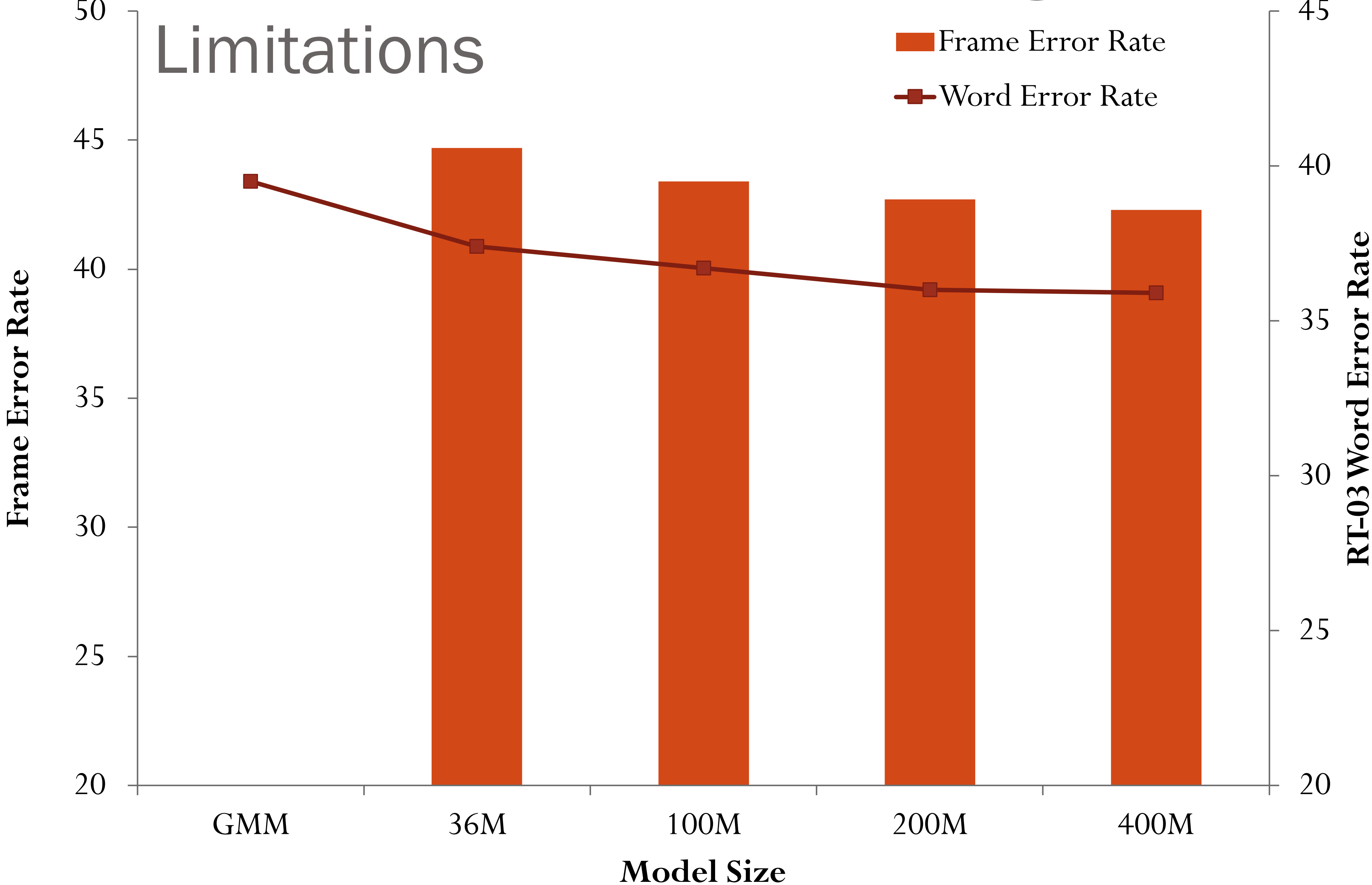


Use a DNN to approximate:
$P(s|x)$

Apply Bayes' Rule:
$P(x|s) = P(s|x) * P(x) / P(s)$

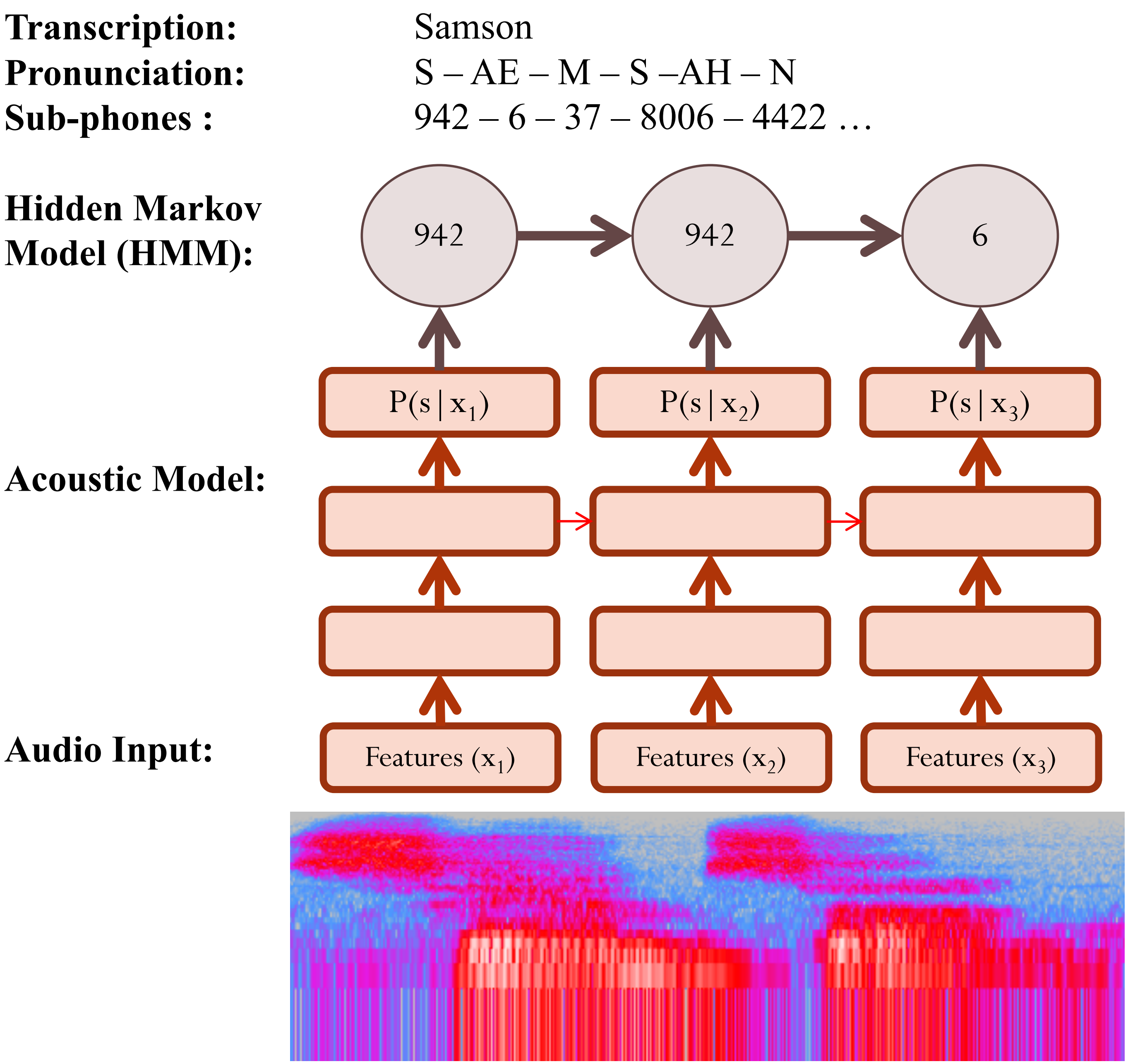
DNN * Constant / State prior

Framework + Isolated Training Limitations

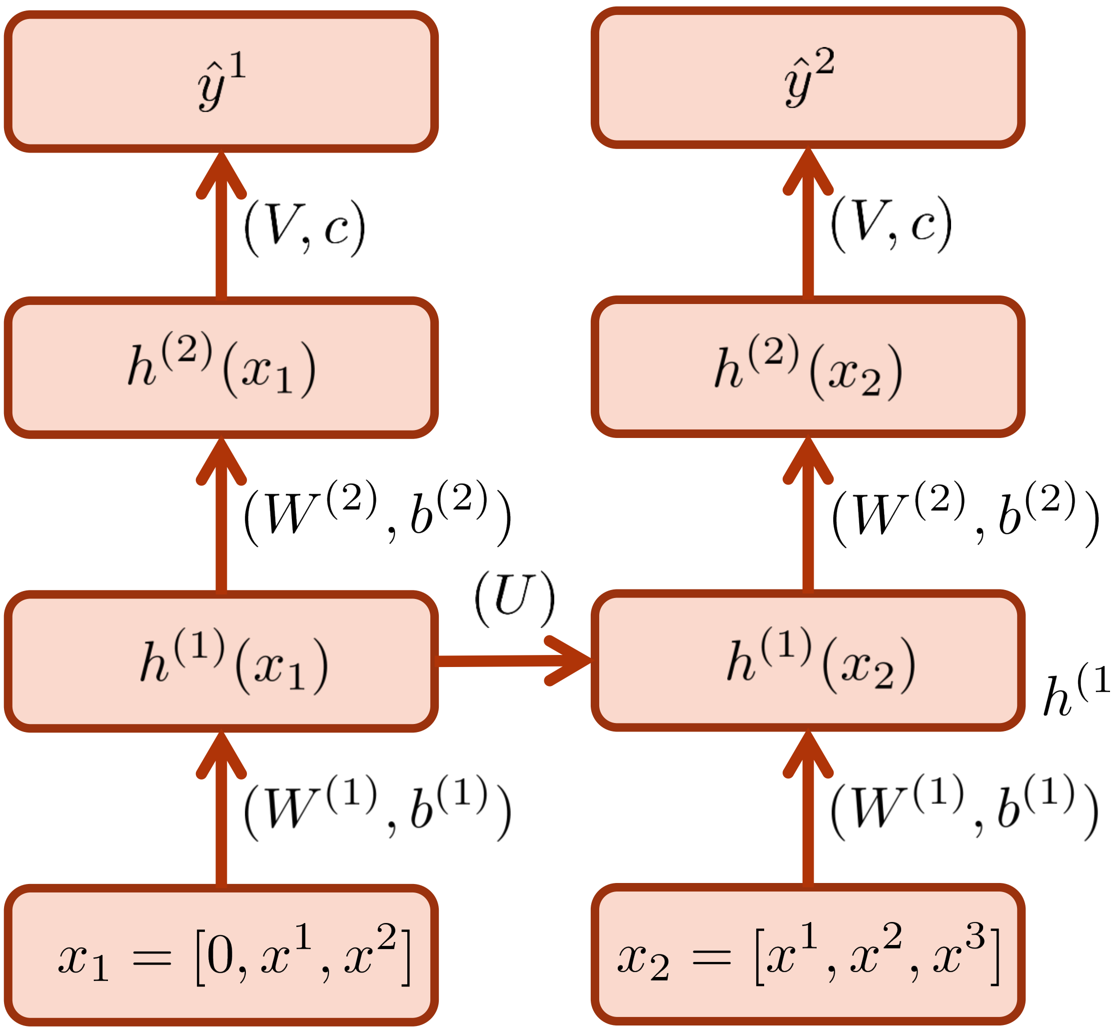


(Maas, Qi, Xie, Hannun, Lengerich, Jurafsky, & Ng. 2017)

Recurrent DNN Hybrid Acoustic Models



Deep Recurrent Network



Output Layer

$$\hat{y}^2 = Vh^{(1)}(x_2) + c$$

Hidden Layer

$$h^{(2)}(x_2) = \sigma(W^{(2)}h^{(1)}(x_2) + b^{(2)})$$

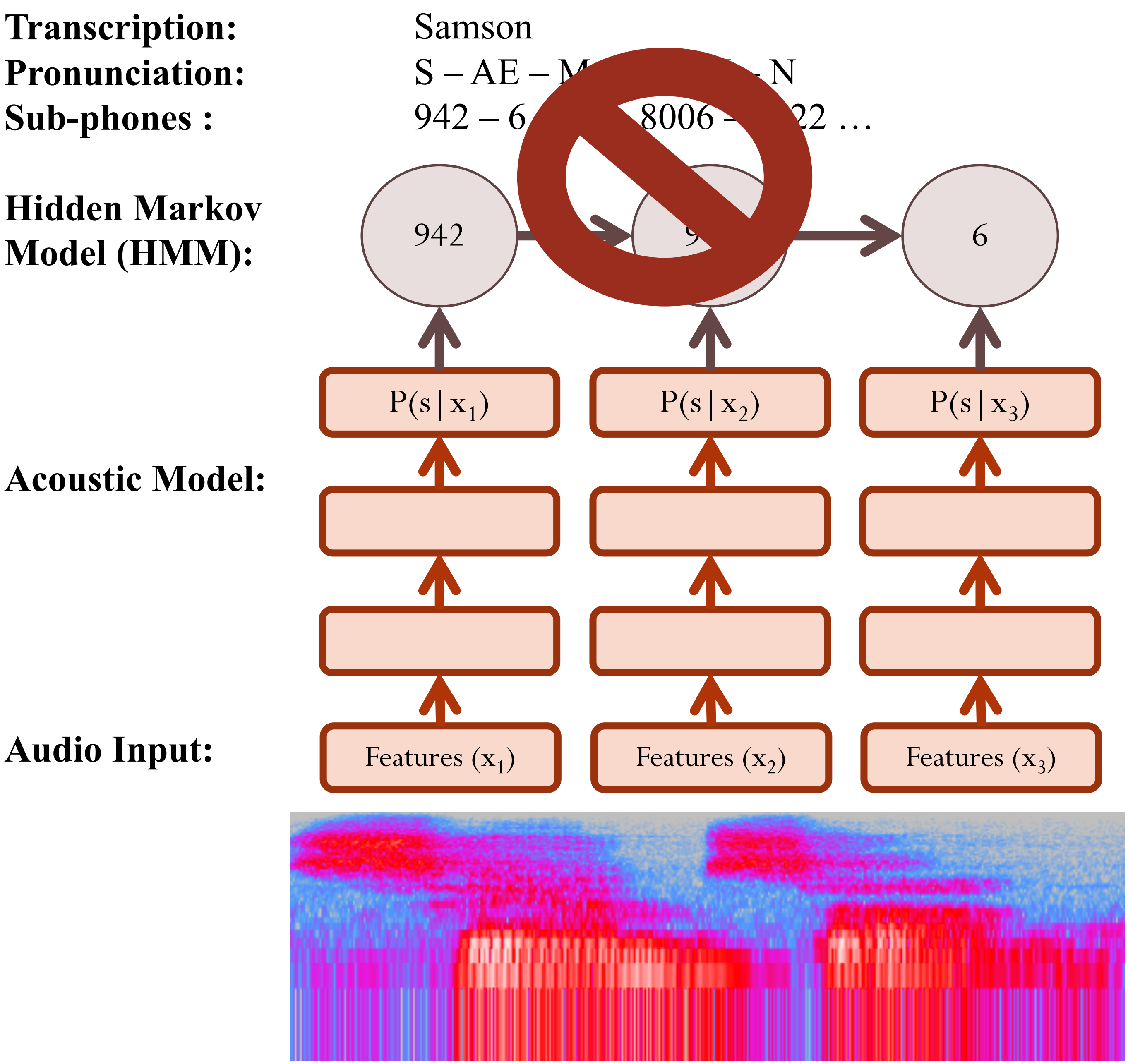
Hidden Layer

$$h^{(1)}(x_2) = \sigma(W^{(1)}x_2 + b^{(1)} + Uh^{(1)}(x_1))$$

Input

$\mathbf{X}$

HMM-Free Recognition



(Graves & Jaitly. 2014)

HMM-Free Recognition

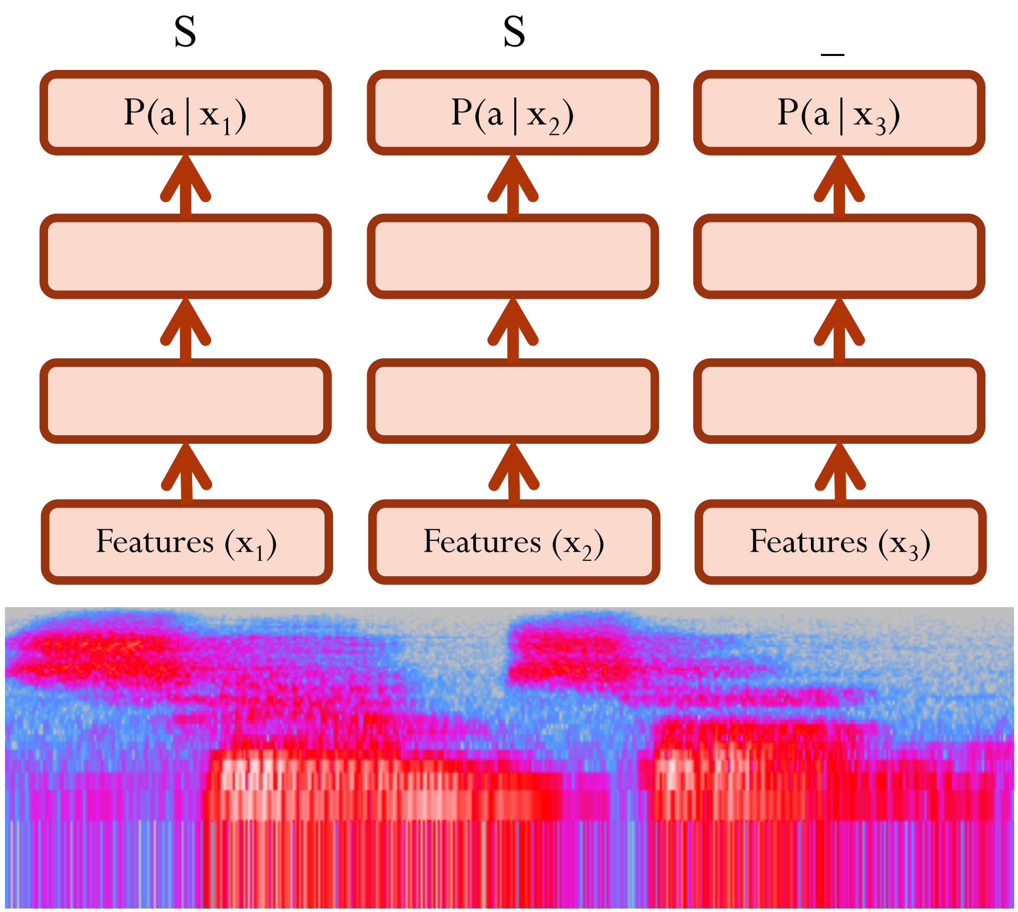
Transcription: Samson

Characters: SAMSON

Collapsing function: SS___AA_M_S___O___NNNN

Acoustic Model:

Audio Input:



Use a DNN to approximate: P(a|x)

The distribution over *characters*

(Graves & Jaitly. 2014)

Example Results (WSJ)

YET A REHBILITATION CRU IS ONHAND IN THE BUILDING LOOGGING BRICKS PLASTER AND BLUEPRINS FOUR FORTY TWO NEW BETIN EPARTMENTS

YET A REHABILITATION CREW IS ON HAND IN THE BUILDING LUGGING BRICKS PLASTER AND BLUEPRINTS FOR FORTY TWO NEW BEDROOM APARTMENTS

THIS PARCLE GUNA COME BACK ON THIS ILAND SOM DAY SOO

THE SPARKLE GONNA COME BACK ON THIS ISLAND SOMEDAY SOON

TRADE REPRESENTIGD JUIDER WARANTS THAT THE U S WONT BACKCOFF ITS PUSH FOR TRADE BARIOR REDUCTIONS

TRADE REPRESENTATIVE YEUTTER WARNS THAT THE U S WONT BACK OFF ITS PUSH FOR TRADE BARRIER REDUCTIONS

TREASURY SECRETARY BAGER AT ROHIE WOS IN AUGGRAL PRESSED FOUR ARISE IN THE VALUE OF KOREAS CURRENCY

TREASURY SECRETARY BAKER AT ROH TAE WOOS INAUGURAL PRESSED FOR A RISE IN THE VALUE OF KOREAS CURRENCY

Earlier work on CTC with phonemes

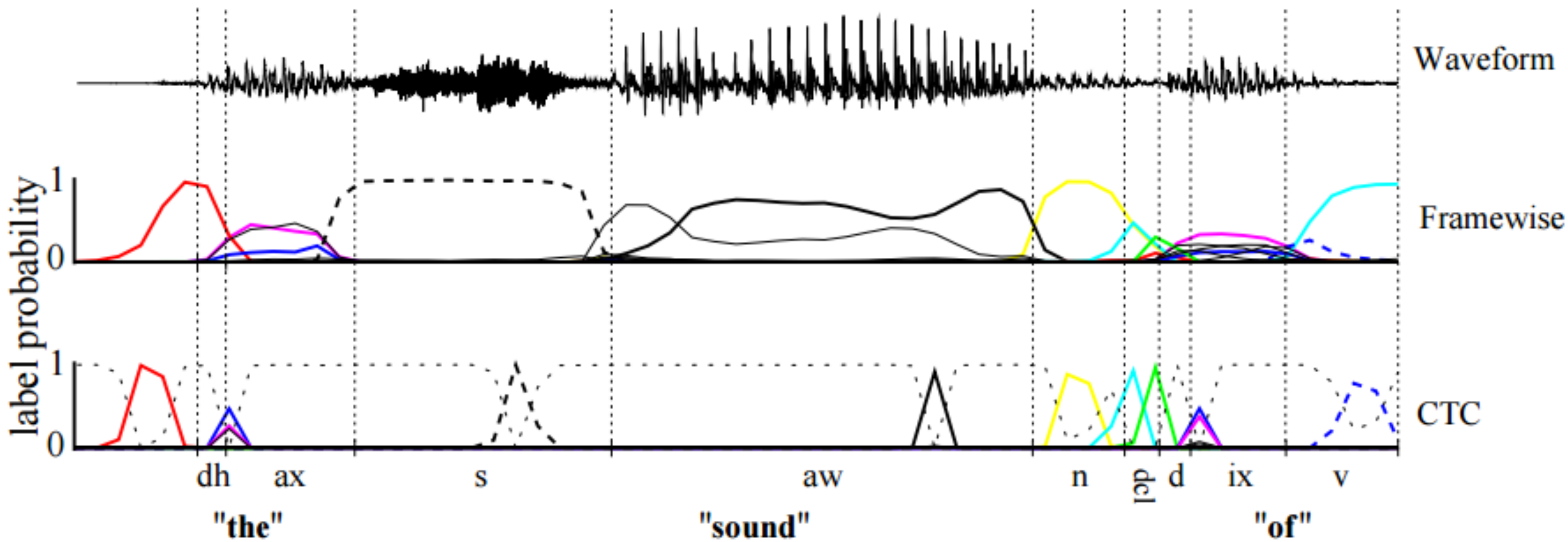


Table 1. **Label Error Rate (LER) on TIMIT**. CTC and hybrid results are means over 5 runs, ± standard error. All differences were significant ($p < 0.01$), except between weighted error BLSTM/HMM and CTC (best path).

System	LER
Context-independent HMM	38.85 %
Context-dependent HMM	35.21 %
BLSTM/HMM	33.84 ± 0.06 %
Weighted error BLSTM/HMM	31.57 ± 0.06 %
CTC (best path)	31.47 ± 0.21 %
CTC (prefix search)	30.51 ± 0.19 %

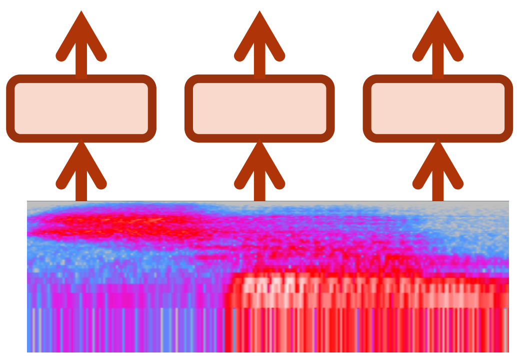
(Graves, Fernández, Gomez, & Schmidhuber. 2006)

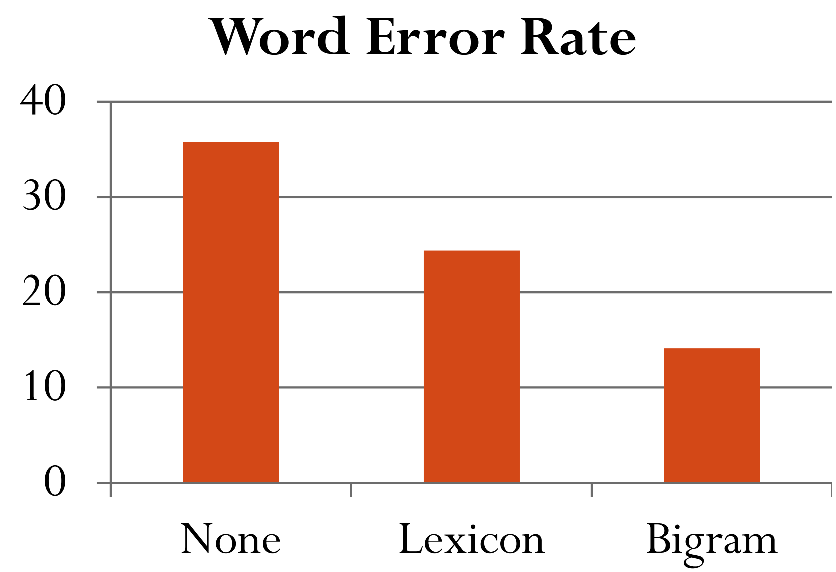
Decoding with a Language Model

Lexicon [a, …, zebra]

Language Model p("yeah" | "oh")

Character Probabilities __oo_h__y_e_aa_h





(Hannun, Maas, Jurafsky, & Ng. 2014)

Loss functions and architecture

- *What function to fit*
- Loss function
- HMM-DNN uses independent per-frame classification with force alignment hard labels
- CTC independent per-frame but cleverly allows for multiple possible labelings

- *How do we approximate that function*
- Neural network architecture
- HMM-DNN typically fine with just DNN
- CTC needs recurrent NN

CTC loss during training

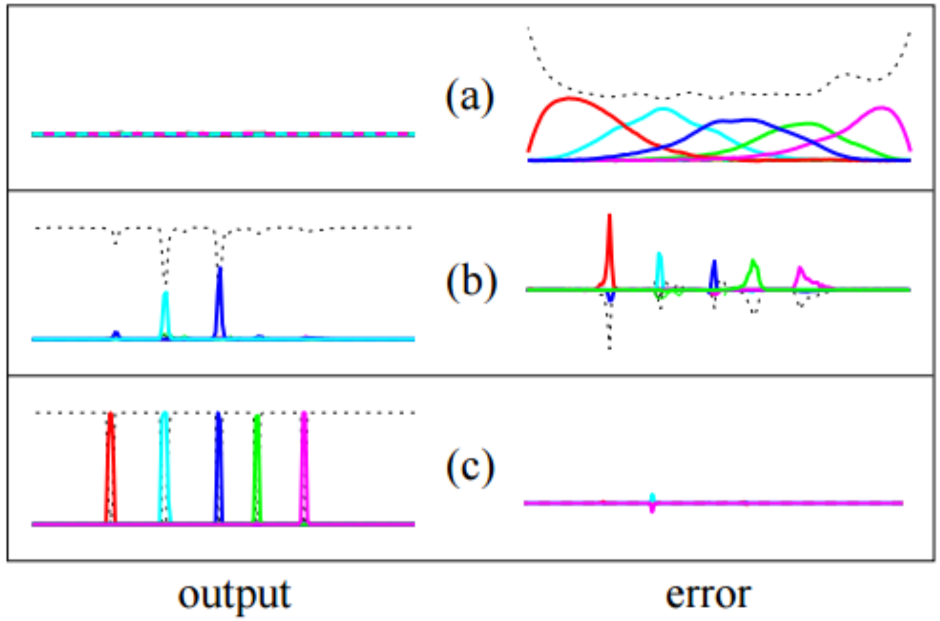
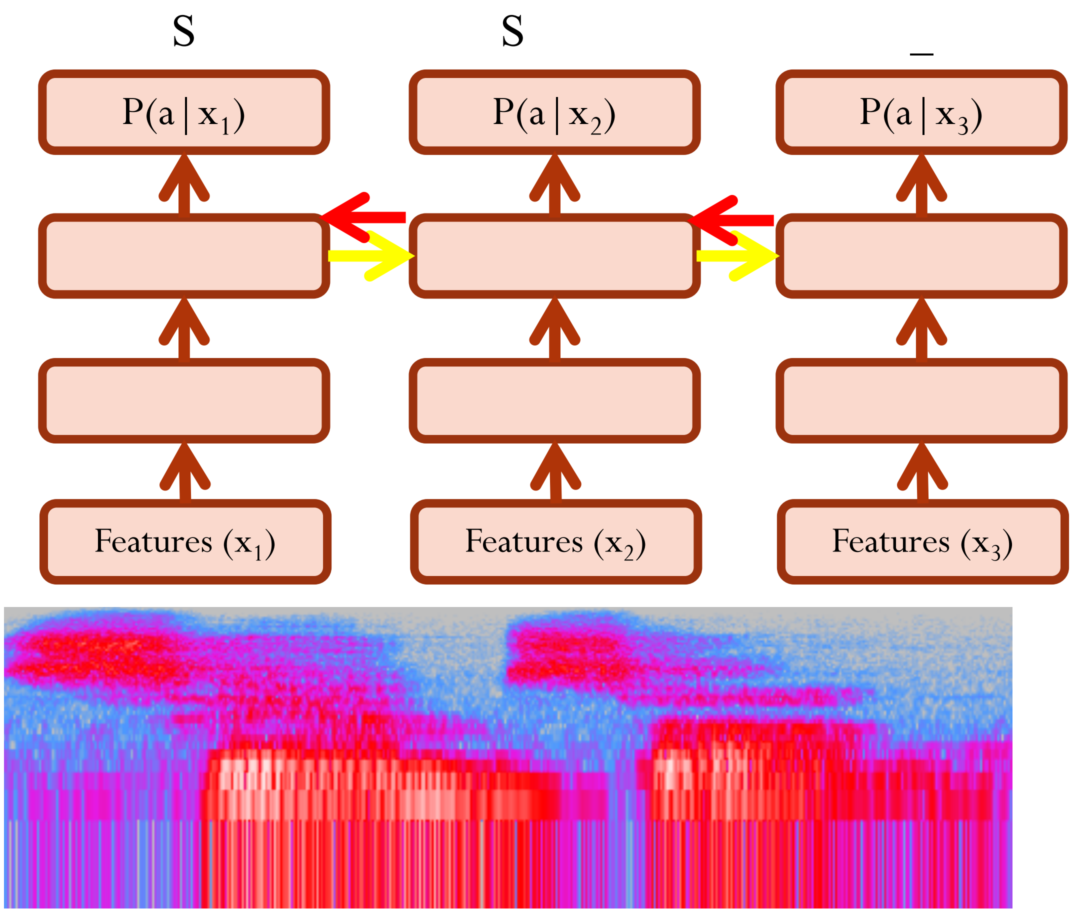


Figure 4. **Evolution of the CTC Error Signal During Training**. The left column shows the output activations for the same sequence at various stages of training (the dashed line is the 'blank' unit); the right column shows the corresponding error signals. Errors above the horizontal axis act to increase the corresponding output activation and those below act to decrease it. (a) Initially the network has small random weights, and the error is determined by the target sequence only. (b) The network begins to make predictions and the error localises around them. (c) The network strongly predicts the correct labelling and the error virtually disappears.

(Graves, Fernández, Gomez, & Schmidhuber. 2006)

Recurrence Matters!



Architecture	CER
DNN	22

(Hannun, Maas, Jurafsky, & Ng. 2014)

CTC Loss Function

- Maximum log likelihood training of transcript
- Intuition: Alignments are unknown so integrate over all possible time-character alignments

$$\mathcal{L}_{\text{CTC}}(X, W) = \sum_{C:\ \kappa(C)=W} p(C|X)$$
$$= \sum_{C:\ \kappa(C)=W} \prod_{t=1}^{T} p(c_t|X).$$

- Example: W = “hi”, T = 3
  possible C such that K(C) = W:
  `hhi`, `hii`, `_hi`, `h_i`, `hi_`

(Graves & Jaitly. 2014)

CTC Objective Function

Labels at each time index are conditionally independent (like HMMs)

$$\Pr(\mathrm{a}|x) = \prod_{t=1}^{T} \Pr(a_t, t|x)$$

Sum over all time-level labelings consistent with the output label.

$$\Pr(y|x) = \sum_{a \in \mathcal{B}^{-1}(y)} \Pr(a|x)$$

Output label: AB

Time-level labelings: AB, _AB, A_B, … _A_B_

Final objective maximizes probability of true labels:

$$CTC(x) = -\log \Pr(y^*|x)$$

(Graves & Jaitly, ICML 2014)

Collapsing Example

Per-frame argmax:

```
______________________________________________________________________________________________________
yy__ee__________tt_ ____________________________________________a______
_rr__e_________hh___________b___ii________lll__i_____tt______aa______tt________iio__n___
___cc_____rrr_u______________________ ________ii___ss
______________o___________nn_____________hhh_a___________________nnddd _________________i__n___
__thh_e______ ________________________________________bb_uuii_______llllldd____ii____nng______
____________________________________l___o___o_g__g___ii____nng______
____b___rr_ii________ck__s__________________________________________p___ll__a________sstt_________eerr__
______a___nnd_ ___b___lll_uu____ee__pp___r___i_________nnss_
________________f______oou____________rrr_________ ______________f_____oo__rrr__tt_y____
_____t____www_oo__________ ____nn___ew____________________
________________________________________________________b___e_______t___________i____n___
____e_________pp_____aa___rr___tt____mm_ee___nnntss
______________________________________________________________________________________________________
__________________________________
```

After collapsing:

yet a rehbilitation cru is onhand in the building loogging bricks plaster and blueprins four forty two new betin epartments

Reference:

yet a rehabilitation crew is on hand in the building lugging bricks plaster and blueprints for forty two new bedroom apartments

Rethinking Decoding

Out of Vocabulary Words

syriza

bae

abo--

sof--

schmidhuber

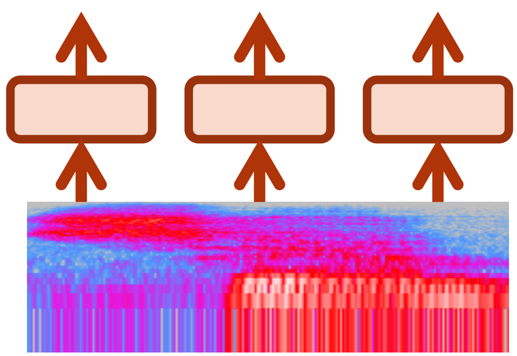
Le [zebra]

L uage (“y | “oh”)

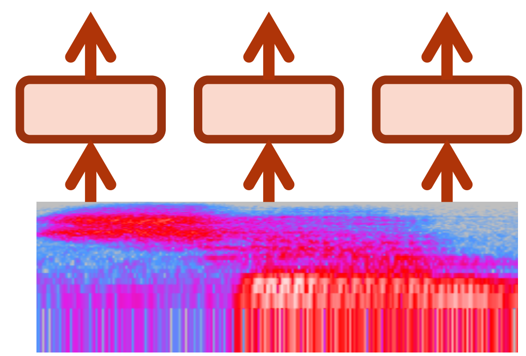
M

***Character* Language Model** p(h | o,h, ,y,e,a,)

Character Probabilities __oo_h__y_e_aa_h



Character Probabilities __oo_h__y_e_aa_h

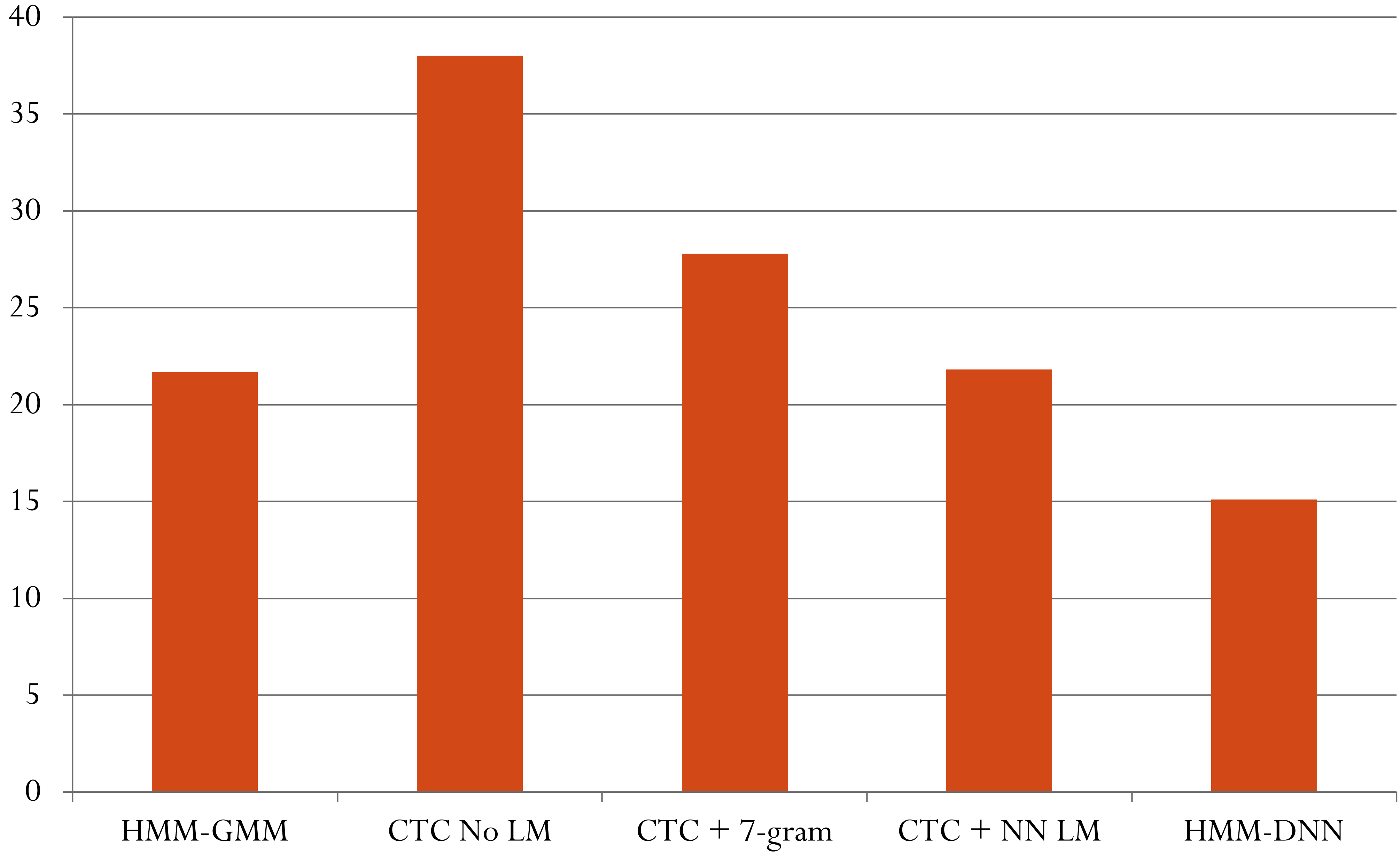


(Maas*, Xie*, Jurafsky, & Ng. 2015)

Beam Search Decoding

Inputs CTC likelihoods $p_{\text{ctc}}(c|x_t)$, character language model $p_{\text{clm}}(c|s)$
Parameters language model weight α, insertion bonus β, beam width k
Initialize $Z_0 \leftarrow \{\varnothing\}$, $p_{\text{b}}(\varnothing|x_{1:0}) \leftarrow 1$, $p_{\text{nb}}(\varnothing|x_{1:0}) \leftarrow 0$
for $t = 1, \ldots, T$ **do**
  $Z_t \leftarrow \{\}$
  for s **in** Z_{t-1} **do**
    $p_{\text{b}}(s|x_{1:t}) \leftarrow p_{\text{ctc}}(\_|x_t)p_{\text{tot}}(s|x_{1:t-1})$ ▷ Handle blanks
    $p_{\text{nb}}(s|x_{1:t}) \leftarrow p_{\text{ctc}}(c|x_t)p_{\text{nb}}(s|x_{1:t-1})$ ▷ Handle repeat character collapsing
    Add s to Z_t
    for c **in** ζ' **do**
      $s^+ \leftarrow s + c$
      if $c \neq s_{t-1}$ **then**
        $p_{\text{nb}}(s^+|x_{1:t}) \leftarrow p_{\text{ctc}}(c|x_t)p_{\text{clm}}(c|s)^\alpha p_{\text{tot}}(c|x_{1:t-1})$
      else
        $p_{\text{nb}}(s^+|x_{1:t}) \leftarrow p_{\text{ctc}}(c|x_t)p_{\text{clm}}(c|s)^\alpha p_{\text{b}}(c|x_{1:t-1})$ ▷ Repeat characters have "_" between
      end if
      Add s^+ to Z_t
    end for
  end for
  $Z_t \leftarrow k$ most probable s by $p_{\text{tot}}(s|x_{1:t})|s|^\beta$ in Z_t ▷ Apply beam
end for
Return $\arg\max_{s \in Z_t}\ p_{\text{tot}}(s|x_{1:T})|s|^\beta$

Lexicon-Free & HMM-Free on Switchboard



(Maas*, Xie*, Jurafsky, & Ng. 2015)

Example Results (Switchboard) ~19% CER

i i don'tknow i don't know what the rain force have to do with it but you know their chop a those down af the tr minusrat everyday

i- i don't kn- i don't know what the rain forests have to do with it but you know they're chopping those down at a tremendous rate everyday

come home and get back in to regular cloos aga

come home and get back into regular clothes again

i guess down't here u we just recently move to texas so my wor op has change quite a bit muh we ook from colorado were and i have a cloveful of sweatterso tuth

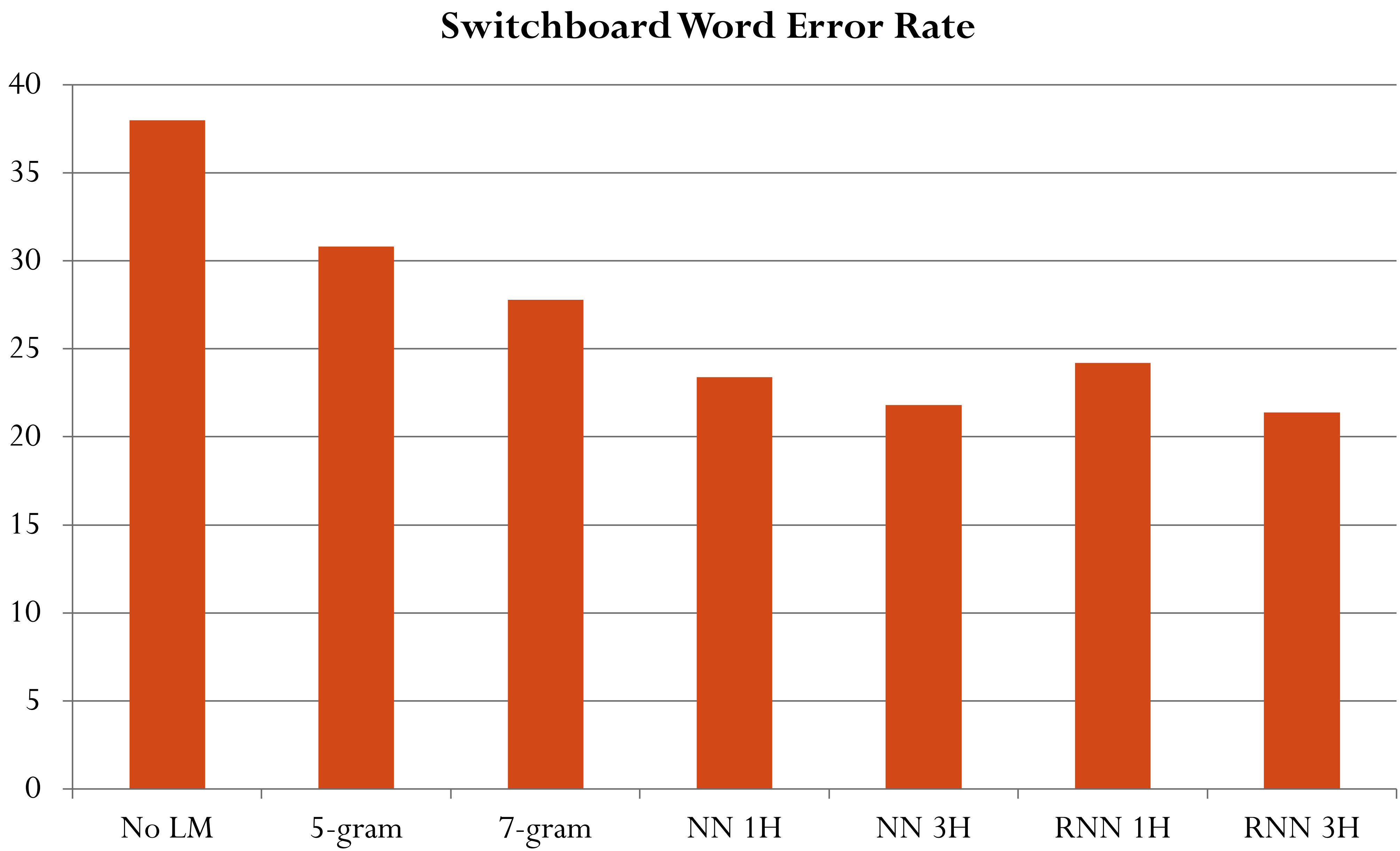
i guess down here uh we just recently moved to texas so my wardrobe has changed quite a bit um we moved from colorado where and i have a closet full of sweaters that

i don't know whether state lit state hood whold itprove there a conomy i don't i don't know that to that the actove being a state

i don't know whether state woul- statehood would improve their economy i don't i don't know that the ve- the act of being a state

(Maas*, Xie*, Jurafsky, & Ng. 2015)

Comparing CLMs



All NN models have 5M total parameters

(Maas*, Xie*, Jurafsky, & Ng. 2015)

Transcribing Out of Vocabulary Words

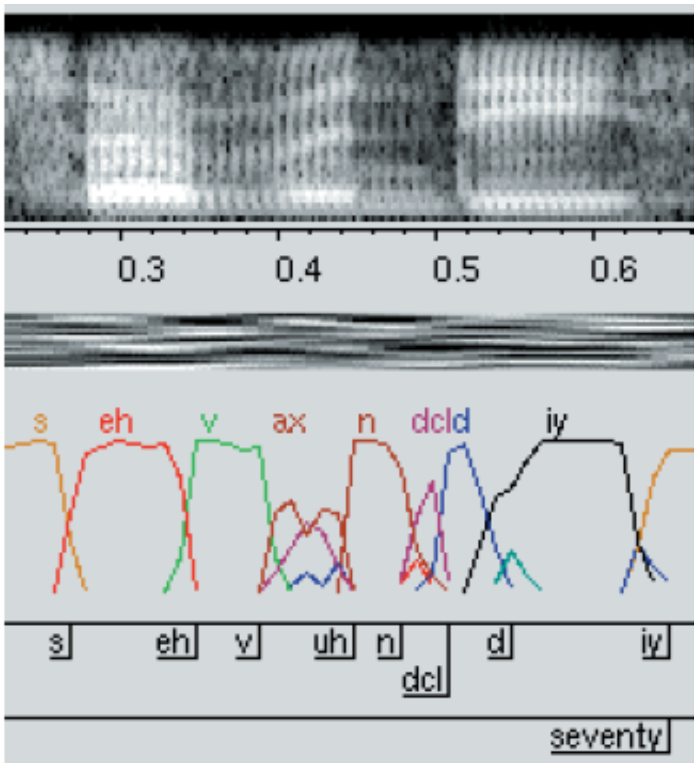
Truth: yeah i went into the i do not know what you think of *fidelity* but
HMM-GMM: yeah when the i don't know what you think of **fidel it even them**
CTC-CLM: yeah i went to i don't know what you think of **fidelity but um**

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**

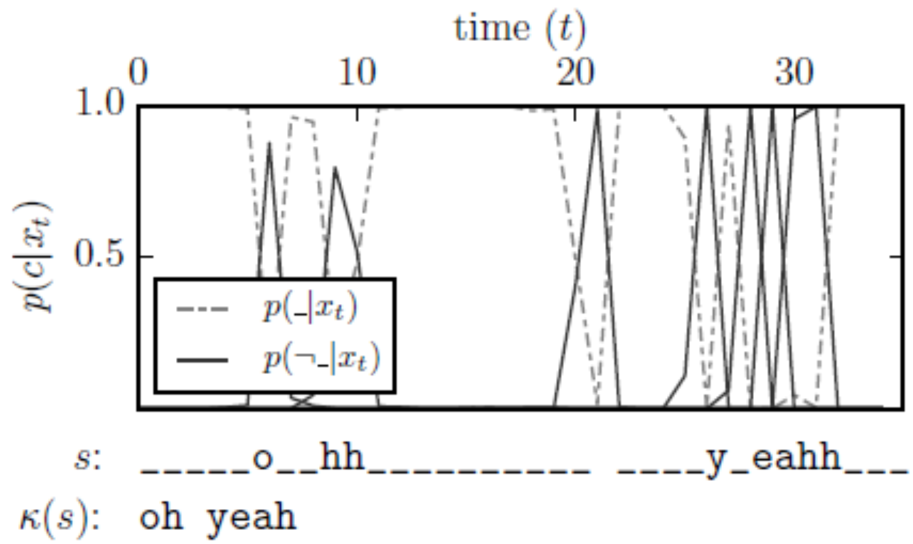
Truth: i would ima- well yeah it is i know you are able to stay home with them
HMM-GMM: i would **amount** well yeah it is i know um you're able to stay home with them
CTC-CLM: i would **ima-** well yeah it is i know uh you're able to stay home with them

(Maas*, Xie*, Jurafsky, & Ng. 2015)

Comparing Alignments



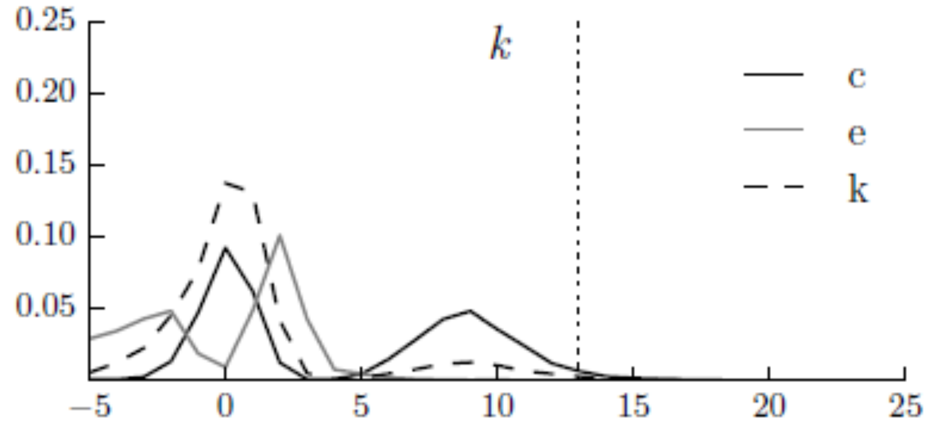
HMM-GMM phone probabilities



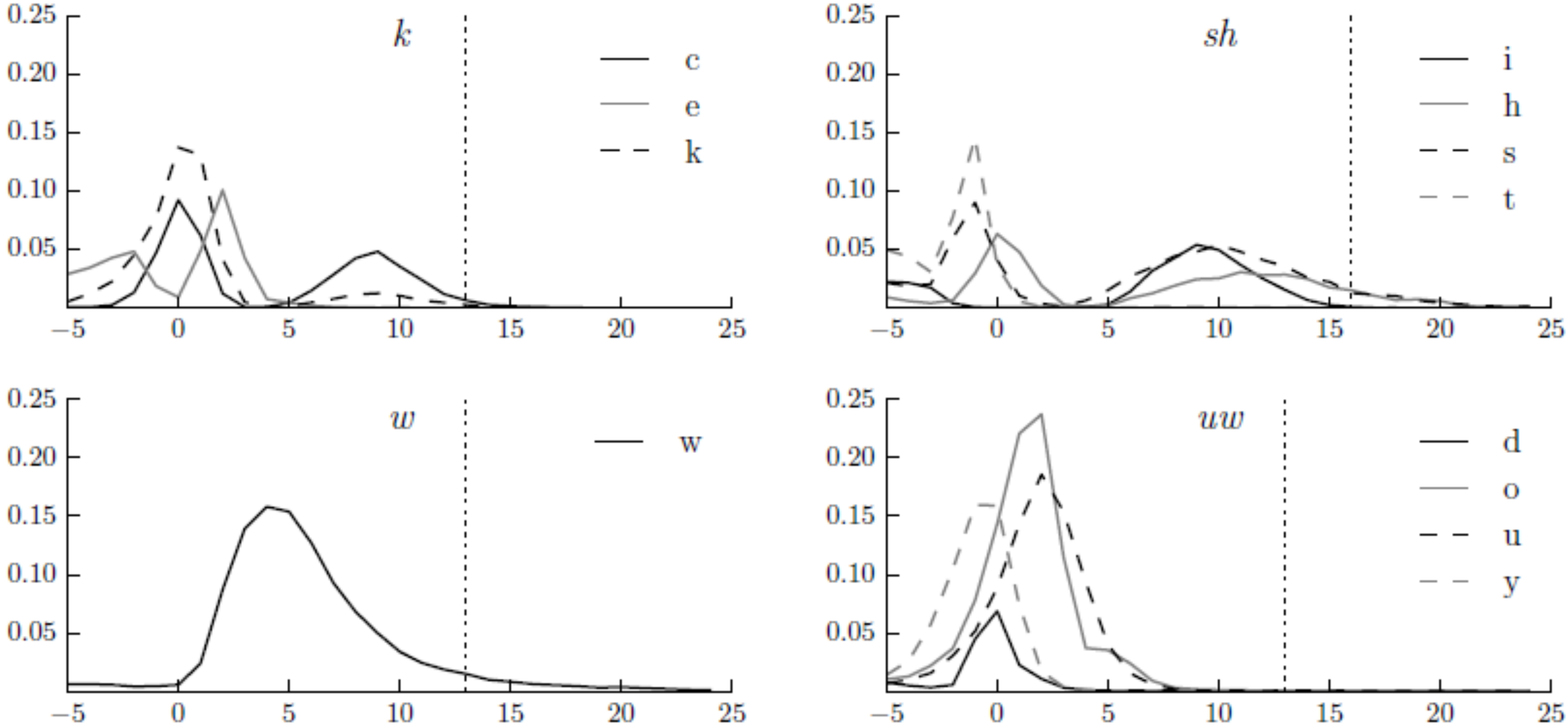
CTC character probabilities

Learning Phonemes and Timing

- Take all phone segments from HMM-GMM alignments (*k*)
- Align all segments to start at the same time = 0
- Compute the average CTC *character* probabilities during the segment (c, e, k)
- Vertical line shows median end time of phone segment from HMM-GMM alignments



Learning Phonemes and Timing



(Maas*, Xie*, Jurafsky, & Ng. 2015)

Scaling end to end models: Baidu deep speech

Dataset	Type	Hours	Speakers
WSJ	read	80	280
Switchboard	conversational	300	4000
Fisher	conversational	2000	23000
Baidu	read	5000	9600

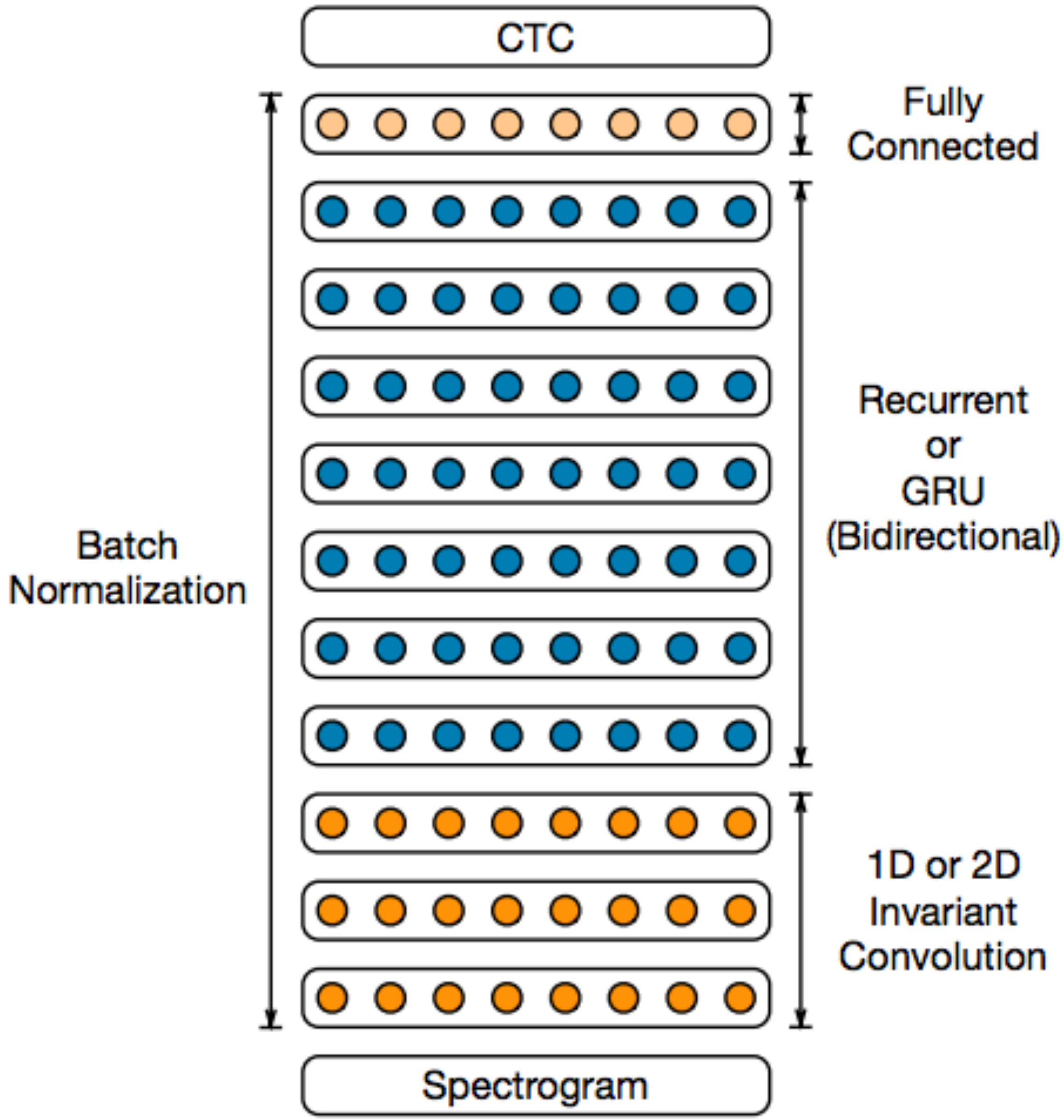
Table 2: A summary of the datasets used to train Deep Speech. The Wall Street Journal, Switchboard and Fisher [3] corpora are all published by the Linguistic Data Consortium.

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**

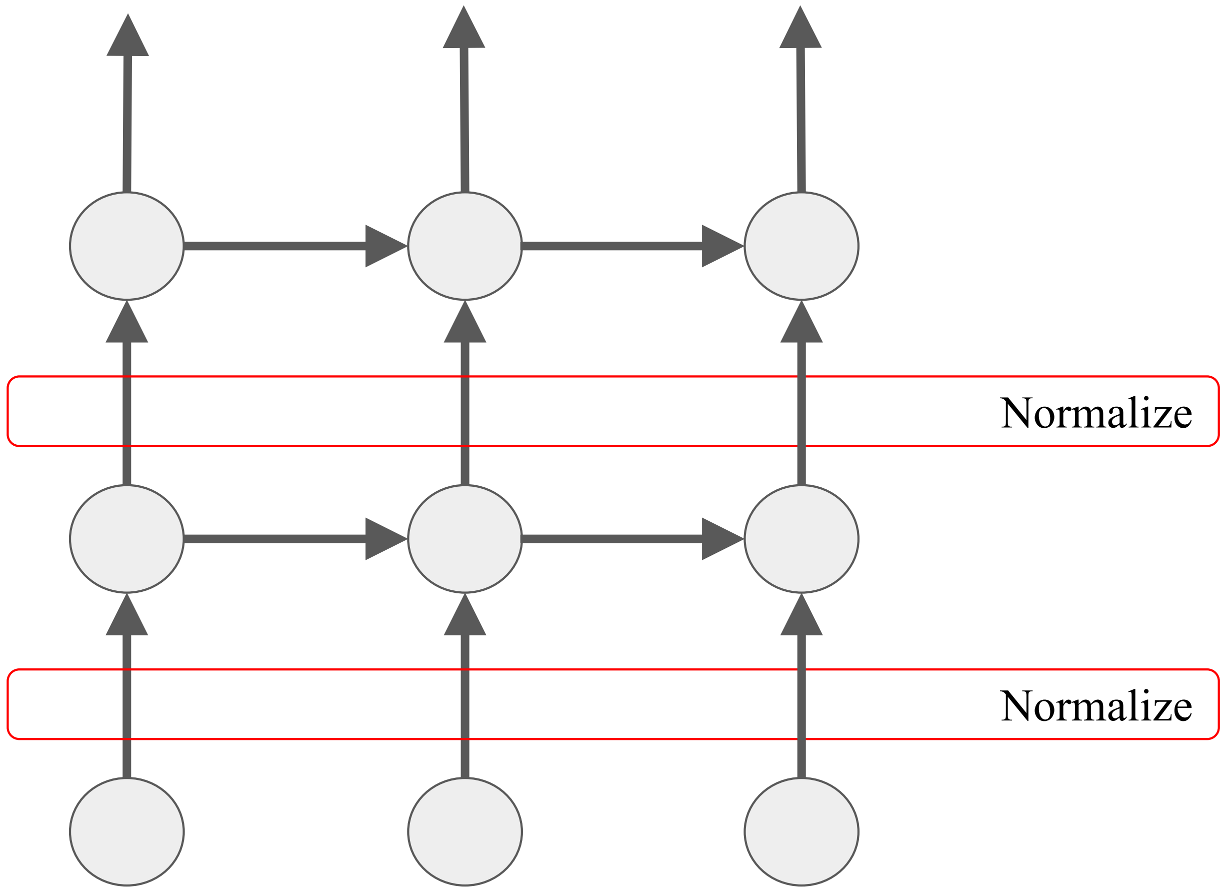
Table 3: Published error rates (%WER) on Switchboard dataset splits. The columns labeled "SWB" and "CH" are respectively the easy and hard subsets of Hub5'00.

(Hannun *et al*. 2014)

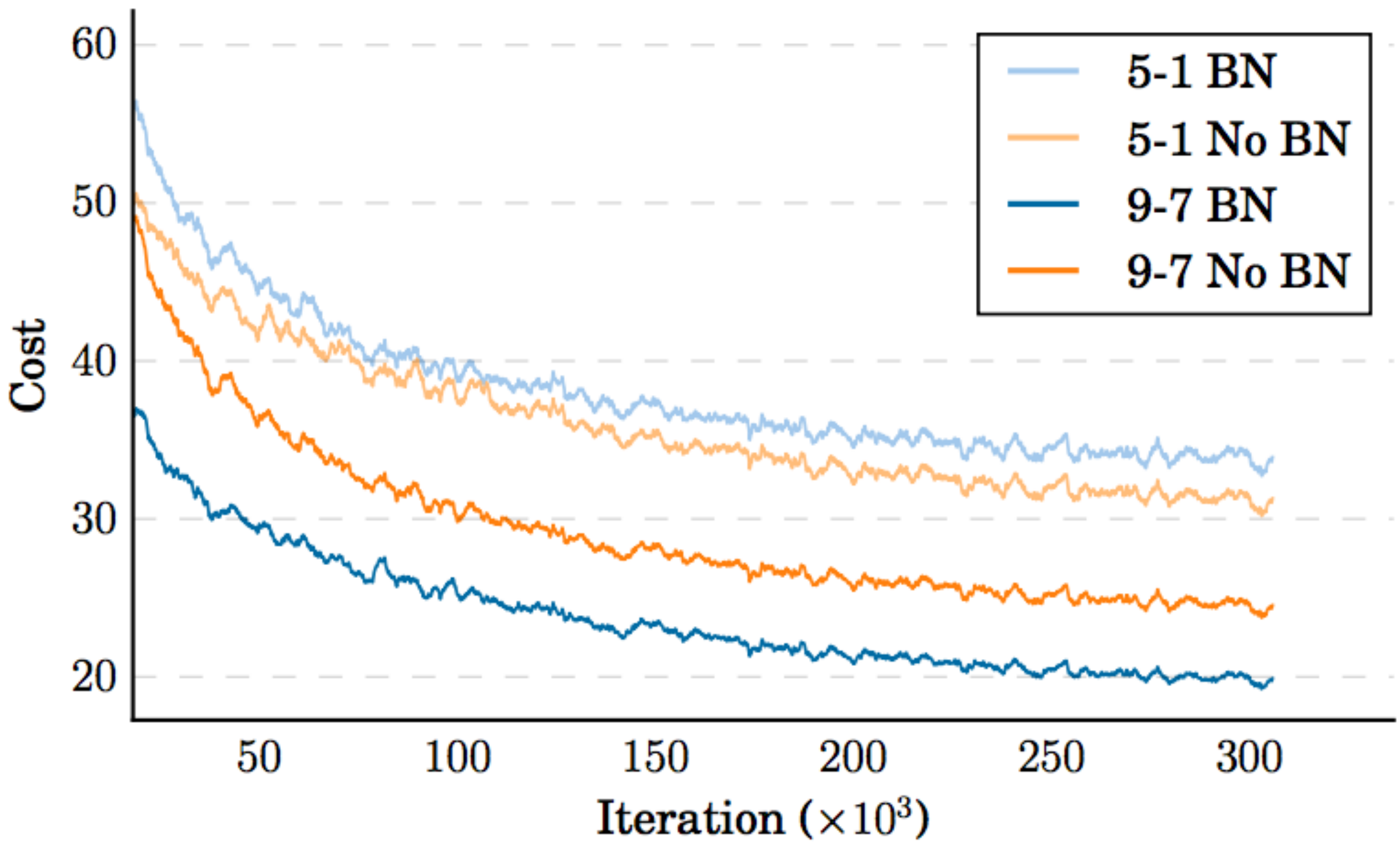
Deep Speech – Deep RNN



Deep Speech – Batch Norm for RNNs



Deep Speech – Batch Norm for RNNs



Slides from Awni Hannun

Deep Speech - Hours of speech data

Language	Hours
English	12,000
Mandarin	10,000

Where does the data come from?

- Public benchmarks (English)
- Internal manually labelled data (English and Mandarin)
- Captioned videos (English and Mandarin)

Deep Speech - Captioned Video Data Pipeline

1. Download publicly available video + captions.

1. Align caption to video with CTC Model

1. Segment at regions of silence

1. Use simple classifier to throw out very noisy samples.

Deep Speech - Captioned Video Data Pipeline

Align with a model trained with CTC?

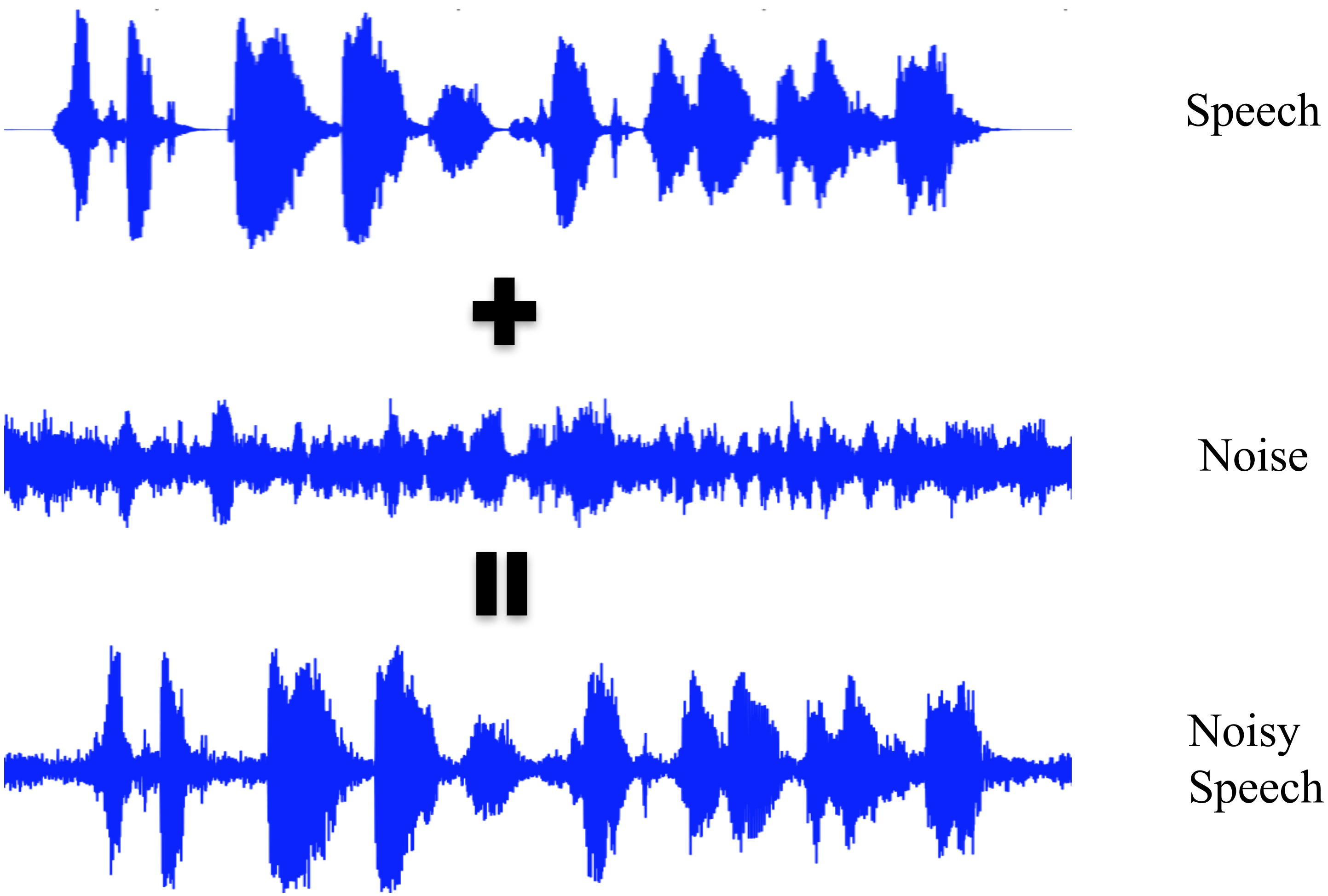
$$\sum_{\ell \in \mathrm{Align}(x,y)} \prod_{t}^{T} p_{\mathrm{ctc}}(\ell_t | x; \theta)$$

$$\downarrow$$

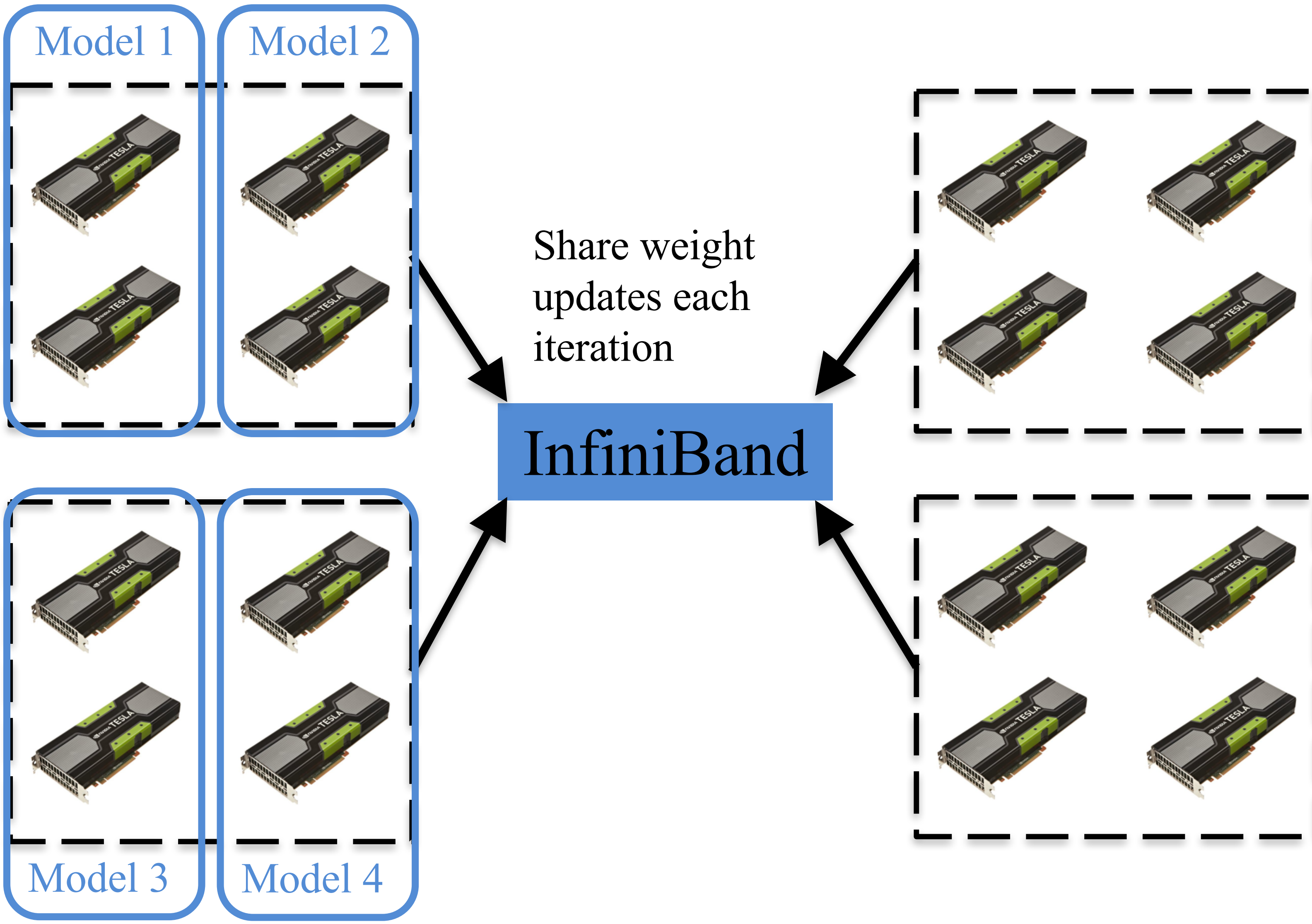
$$\arg\max_{\ell \in \mathrm{Align}(x,y)} \prod_{t}^{T} p_{\mathrm{ctc}}(\ell_t | x; \theta)$$

Deep Speech - Even more data!

Augmentation: noise synthesis, reverb, time-stretching, pitch-shifting,...



Deep Speech – Data Parallel GPU Scaling



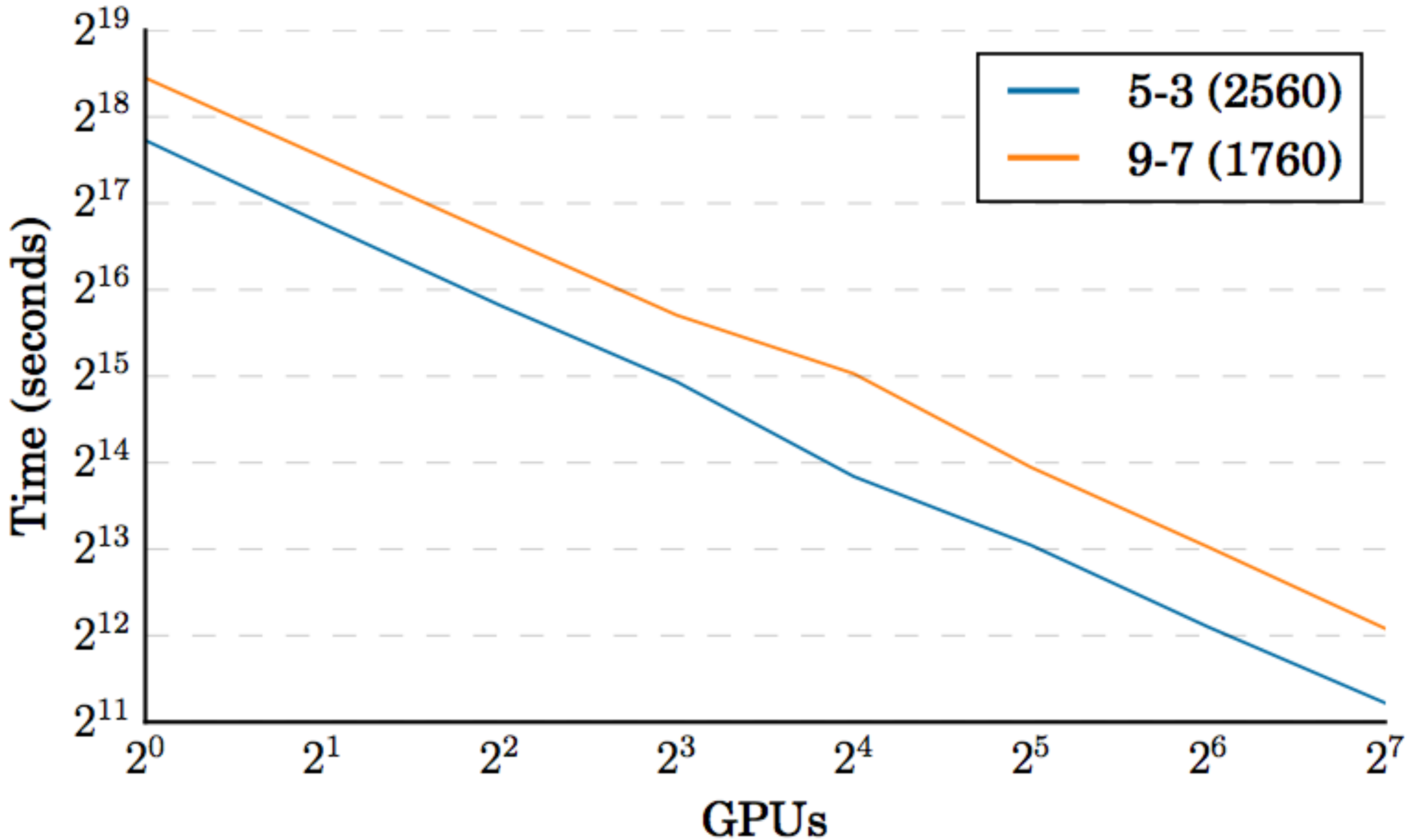
Deep Speech – Data Parallel GPU Scaling

Custom Ring Reduce avoids extraneous copies to CPU memory.

# GPUs	OpenMPI All-reduce (s)*	Custom All-reduce (s)*	Factor Speedup
4	55359	2587	21.4
8	48881	2470	19.8
16	21562	1393	15.5

*Measures time spent in all-reduce for a single epoch.

Deep Speech – Data Parallel GPU Scaling



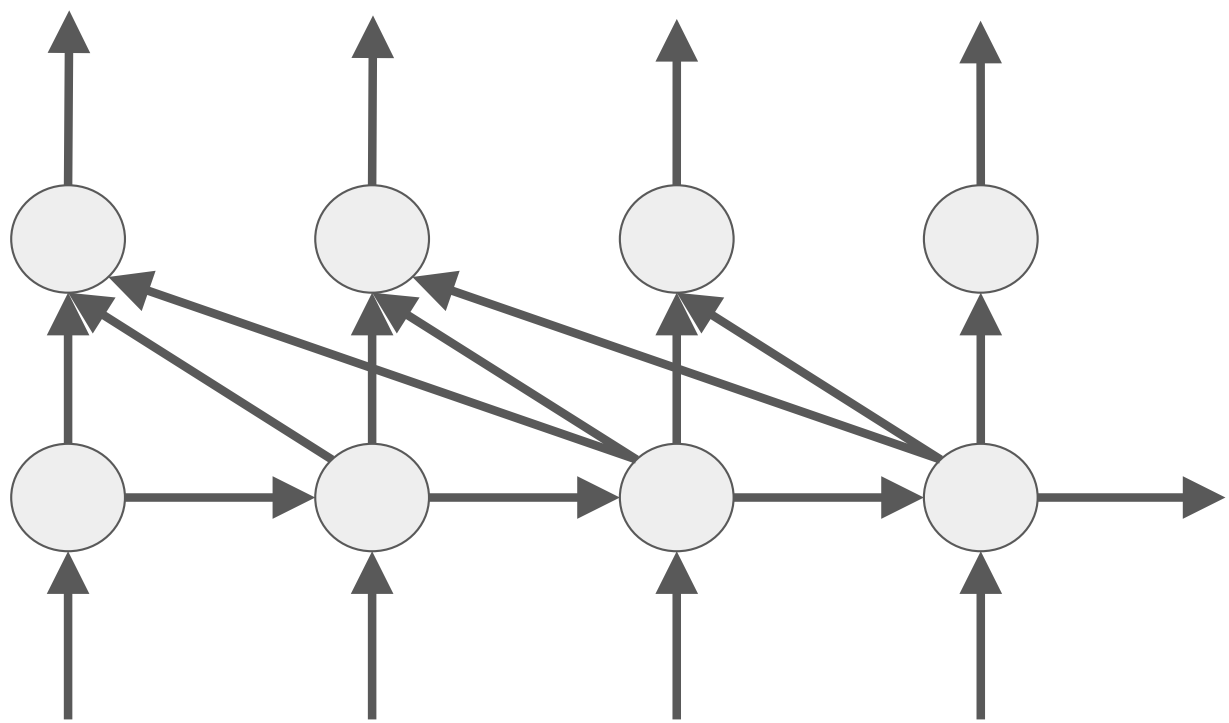
Deep Speech – Some results

Architecture	English (WER)	Mandarin (WER)
5-layer 1-RNN	13.55	15.41
5-layer 3-RNN	11.61	11.85
5-layer 3-RNN + BatchNorm	10.56	9.39
9-layer 7-RNN + BatchNorm + Frequency Convolution	9.52	7.93

Deep Speech – Deployment

- Bi-directional models give almost 10% relative boost … but we can't deploy them.
- ASR latencies for voice search <50ms
- For 3 second audio would need to decode 60x faster than realtime!

Deep Speech – Lookahead convolution



$$\mathbf{h}_t = \sum_{j=1}^{\tau+1} \mathbf{w}_j \odot \mathbf{x}_{t+j-1}$$

Deep Speech – Lookahead convolution

For a lookahead of 20 time-steps (about 800ms in the future)

Model	English (WER)	Chinese (WER)
Forward only	18.8	15.7
Forward + Lookahead (+50k params)	16.8	13.5
Bidirectional (+12M params)	15.4	12.8

Listen, Attend, and Spell

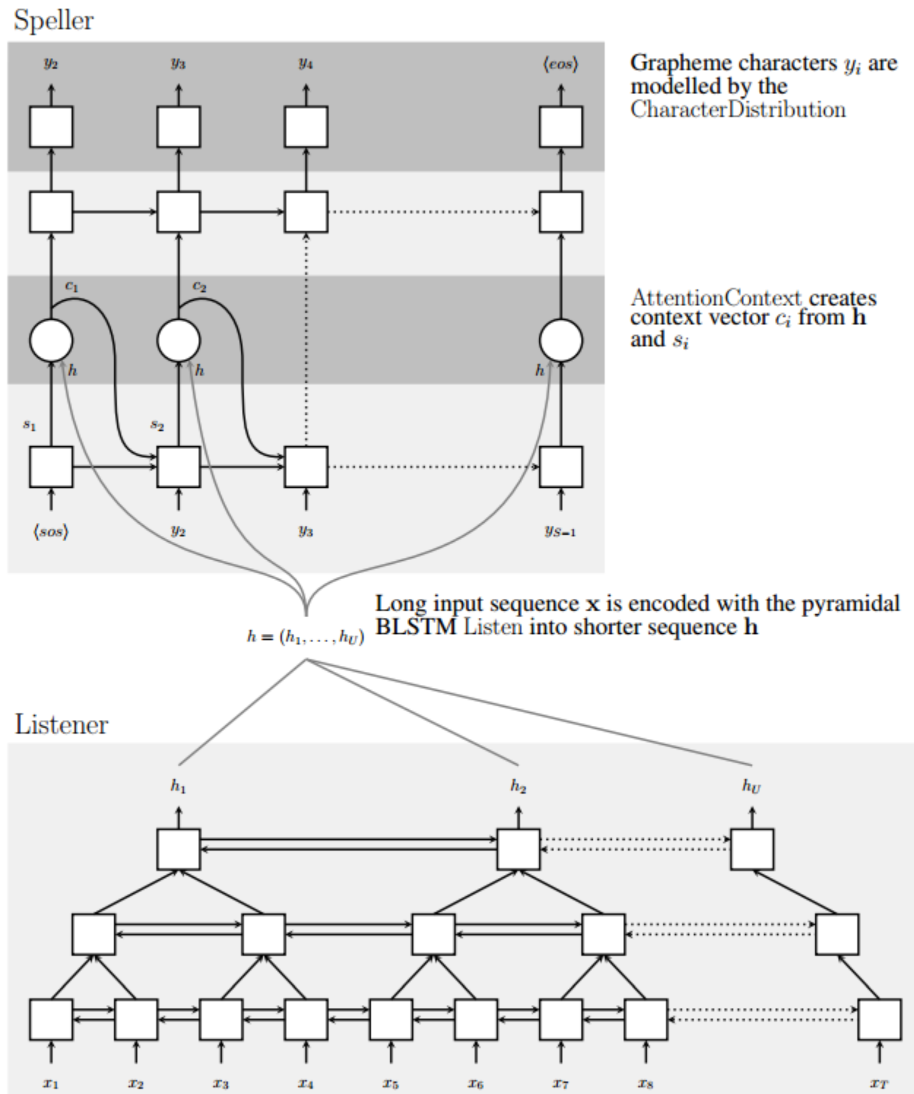
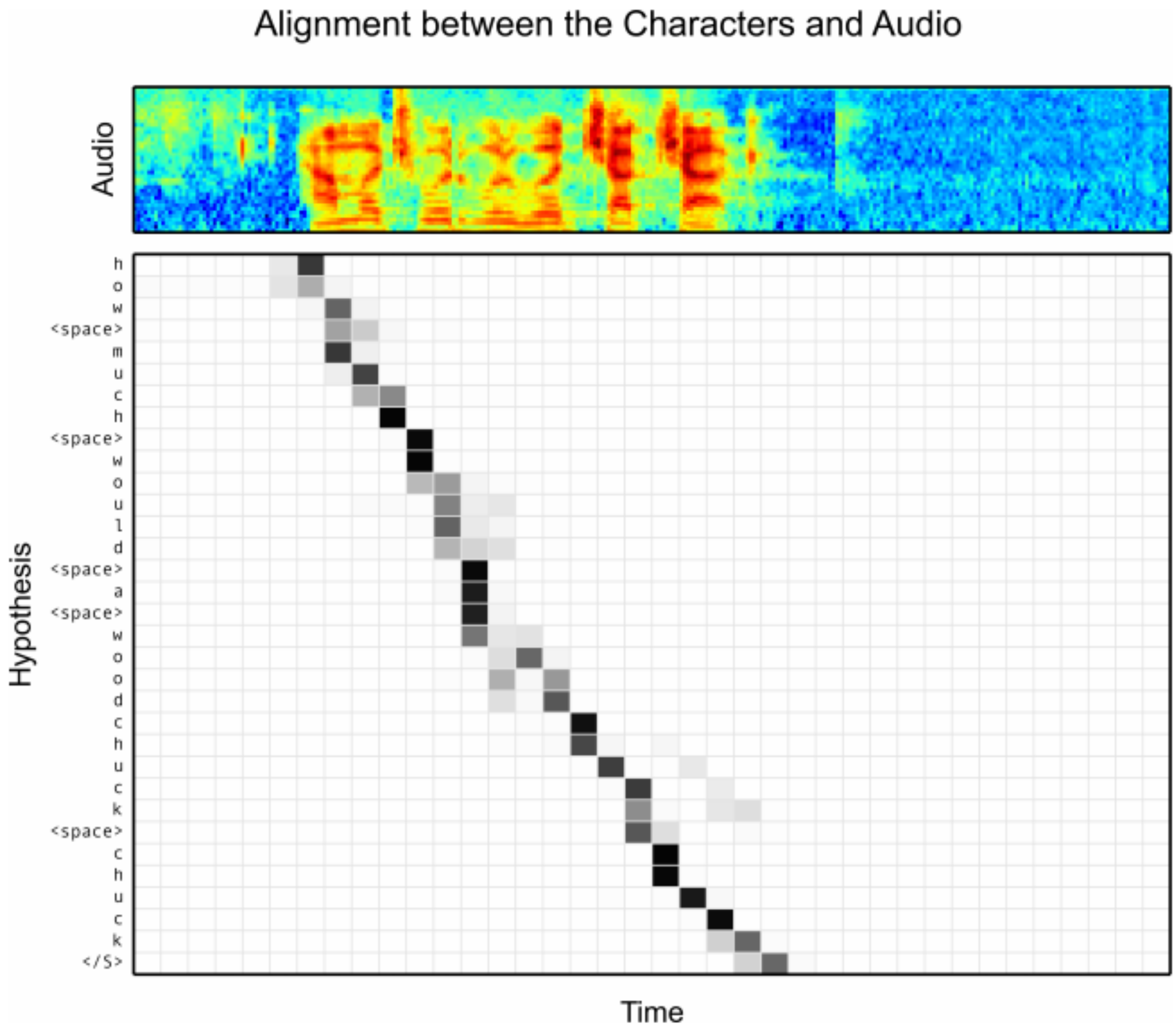


Figure 1: Listen, Attend and Spell (LAS) model: the listener is a pyramidal BLSTM encoding our input sequence $\mathbf{x}$ into high level features $\mathbf{h}$, the speller is an attention-based decoder generating the $\mathbf{y}$ characters from $\mathbf{h}$.

(Chan, Jaitly, Le, & Vinyals. 2015)

Listen, Attend, and Spell



(Chan, Jaitly, Le, & Vinyals. 2015)

Listen, Attend, and Spell

Table 1: WER comparison on the clean and noisy Google voice search task. The CLDNN-HMM system is the state-of-the-art system, the Listen, Attend and Spell (LAS) models are decoded with a beam size of 32. Language Model (LM) rescoring was applied to our beams, and a sampling trick was applied to bridge the gap between training and inference.

Model	Clean WER	Noisy WER
CLDNN-HMM [20]	8.0	8.9
LAS	16.2	19.0
LAS + LM Rescoring	12.6	14.7
LAS + Sampling	14.1	16.5
LAS + Sampling + LM Rescoring	10.3	12.0

(Chan, Jaitly, Le, & Vinyals. 2015)

Attention-based sequence generation

- Maximum likelihood conditional language model given the aud $p(y_1)\prod_{t=2}^{T} p(y_t|y_1,\cdots,y_{t-1})$

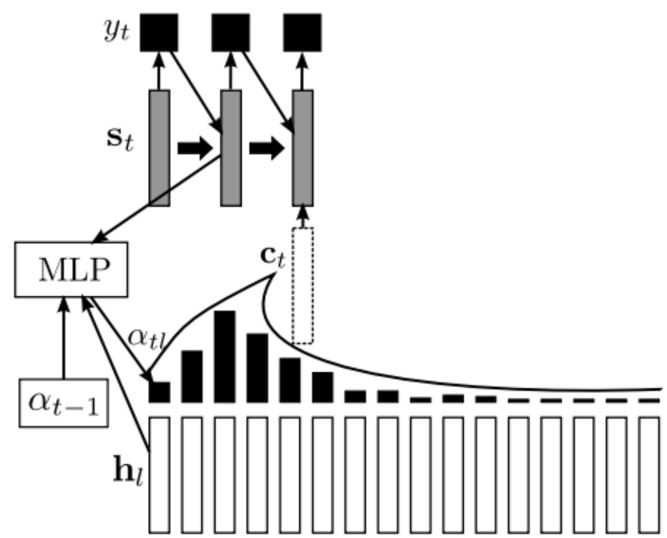


Fig. 3. Schematic representation of the Attention-based Recurrent Sequence Generator. At each time step t, an MLP combines the hidden state $\mathbf{s}_{t-1}$ with all the input vectors $\mathbf{h}_l$ to compute the attention weights α_{tl}. Subsequently, the new hidden state $\mathbf{s}_t$ and prediction for output label y_t can be computed.

(Bahdanau *et al*. 2016)