Algorithms for Speech and Natural Language Processing

from HMMs to end-to-end speech recognition

Courtesy of

Neil Zeghidour

Phd Student, FAIR Paris, CoML (INRIA/ENS)

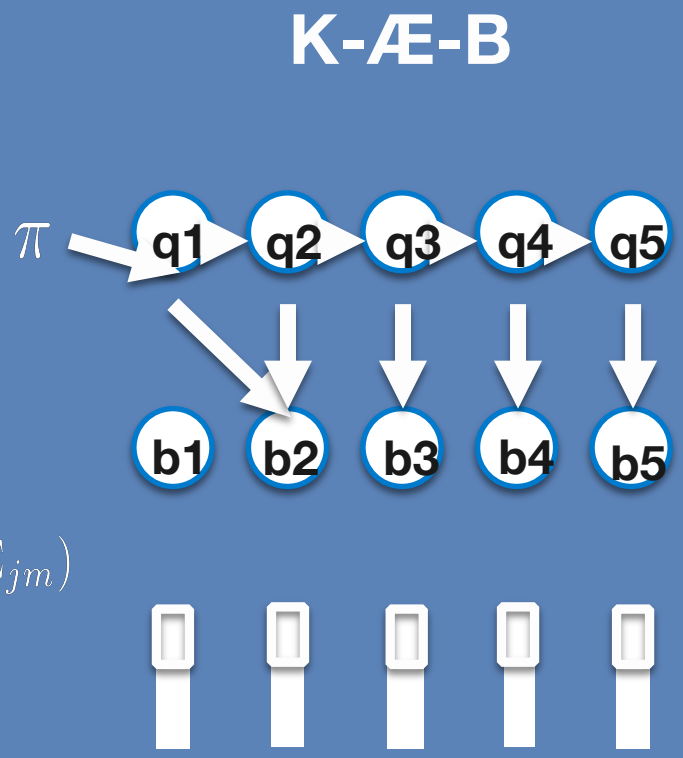
The next hour

- HMM-GMM (recap)
- HMM-DNN, also called hybrid model (rec
- CTC
- Neural language models
- New developments
- Open problems

Recap

Recap

- Extract speech features
- Train a Hidden Markov Model with Gaussian Mixture Model for emissions (HMM-GMM)

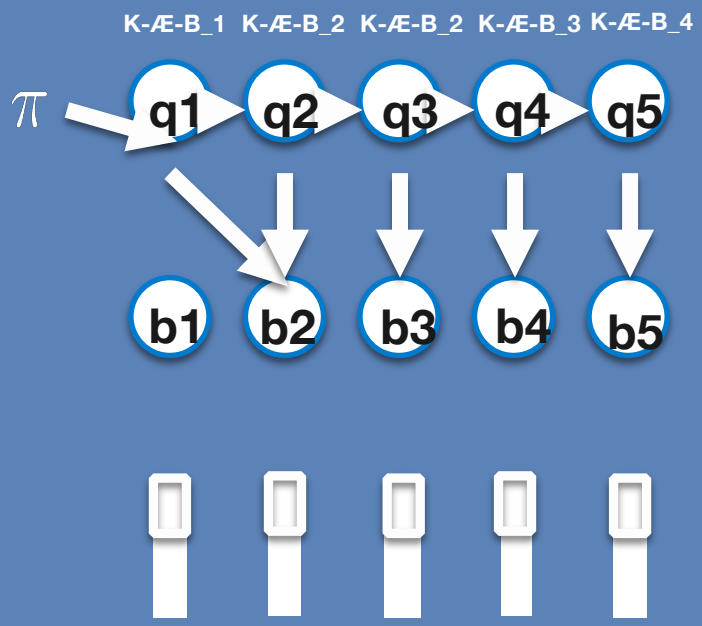


$$b_j \sim \sum_{m=1}^{M} c_{jm} \mathcal{N}(\mu_{jm}, \Sigma_{jm})$$

Recap

Recap

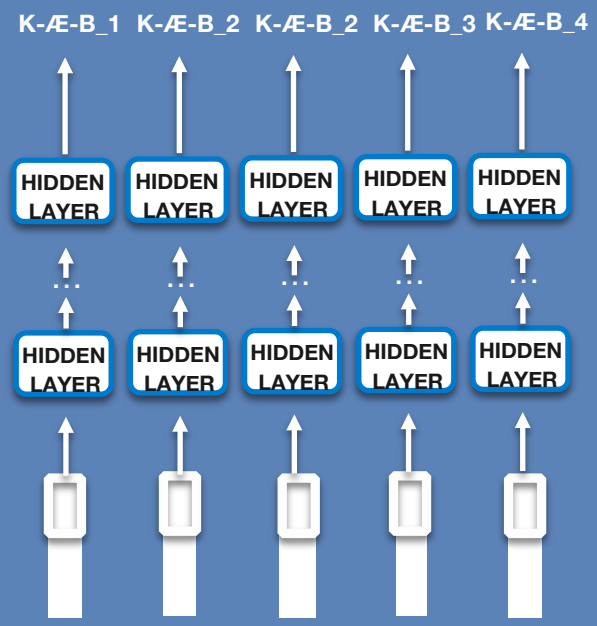
- Extract speech features
- Train a Hidden Markov Model with Gaussian Mixture Model for emissions (HMM-GMM)
- Use the Viterbi algorithm to extract an alignment of feature frames with states



Recap

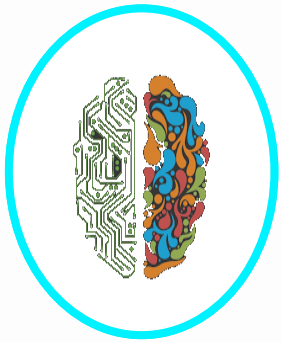
Recap

- Extract speech features
- Train a Hidden Markov Model with Gaussian Mixture Model for emissions (HMM-GMM)
- Use the Viterbi algorithm to extract an alignment of feature frames with states
- Train a Neural Network to predict each state from its frame

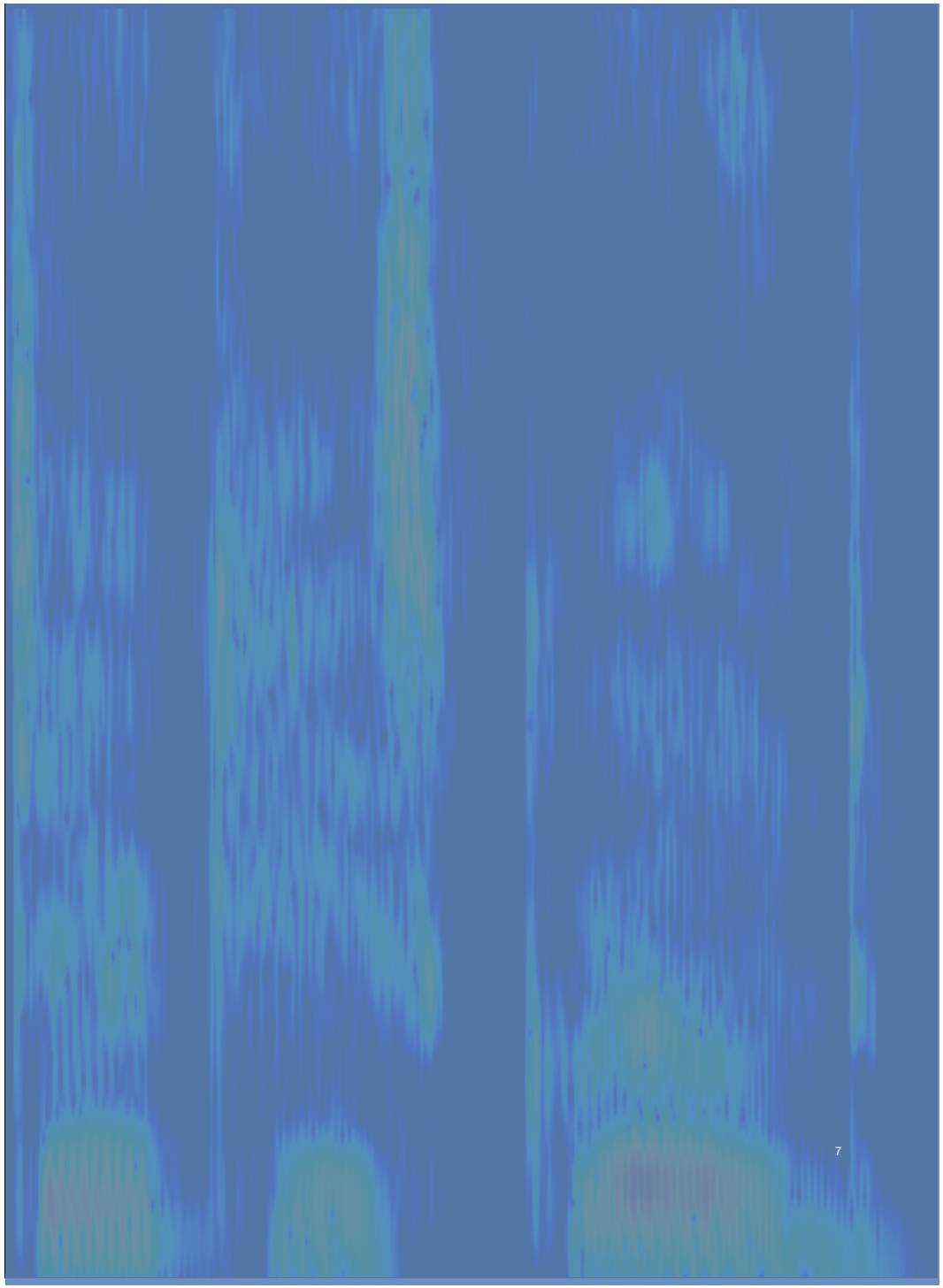


Towards end-to-end training

- One neural network
- No alignment
- No speech features



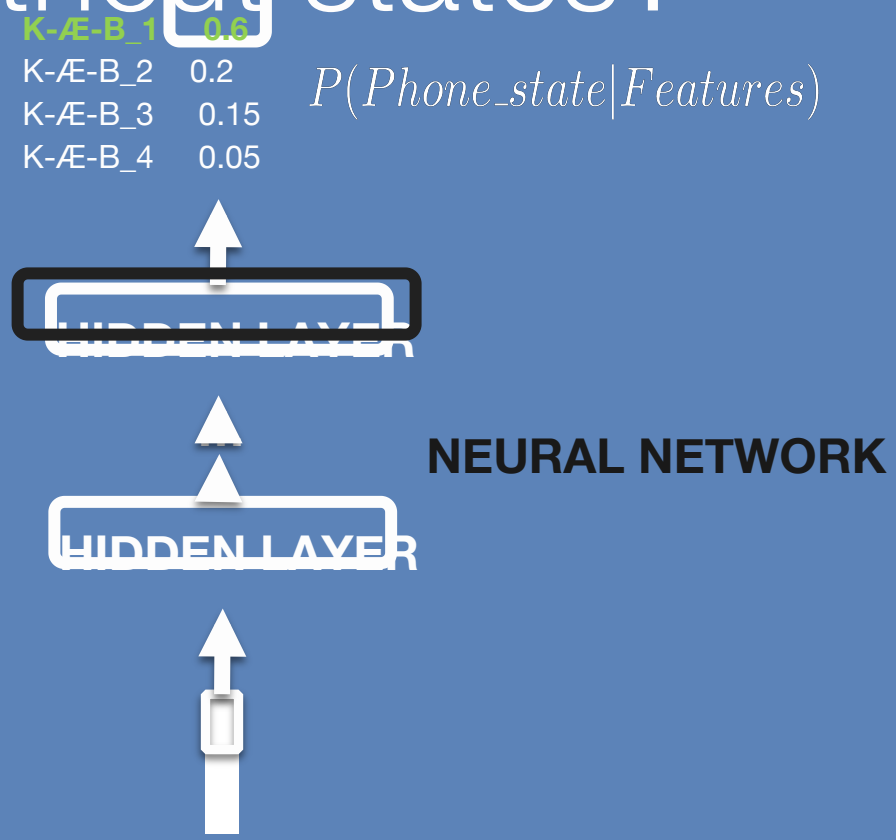
Connectionist Temporal Classification



Connectionnist Temporal Classification

Training a DNN without states?

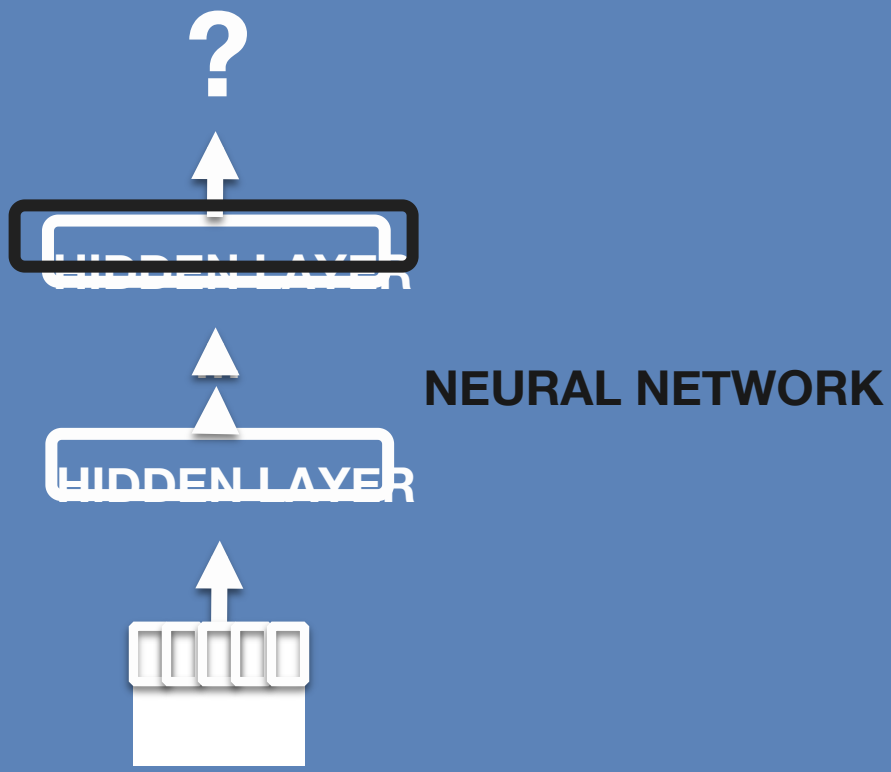
- When a state is attributed to each frame it is trivial to define the loss function: classification loss



Connectionnist Temporal Classification

Training a DNN without states?

- When a state is attributed to each frame it is trivial to define the loss function
- Without alignment, we have the word transcription and the feature frames
- Train a speech recognition system directly from the features to the transcription (no phonetic transcription, no pronunciation dictionary, no alignment)



Connectionnist Temporal Classification

Problem: no alignment available

- Phonemes last dozens to hundreds of miliseconds, while frames are sampled every 10ms
- Many more frames than phonemes/ letters
- We need to learn **classification** and **alignment** jointly
- A loss function allows learning both at the same time: Connectionist Temporal Classification (CTC)

CAB

Connectionnist Temporal Classification

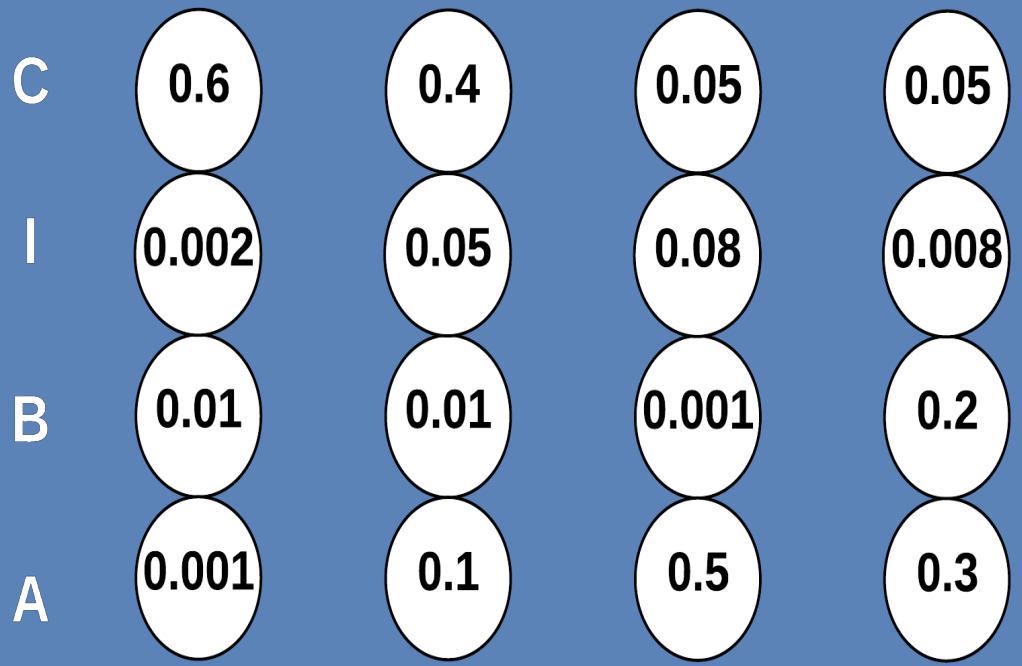
Connectionist Temporal Classification

- Given that the final layer of your network is a softmax with as many dimensions as there are characters, it can be seen as a probability distribution over characters

y_k^t the probability of character k at time t

$$y_k^t = Softmax(h_{N-1}(x_t))$$

$$= \frac{e^{w_k^T h_{N-1}(x_t)+b}}{\sum_{k=1}^{K} e^{w_k^T h_{N-1}(x_t)}}$$



« Connectionist Temporal Classification: Labelling Unsegmented Sequence Data with Recurrent Neural Networks », Graves et al.

Connectionnist Temporal Classification

Connectionist Temporal Classification

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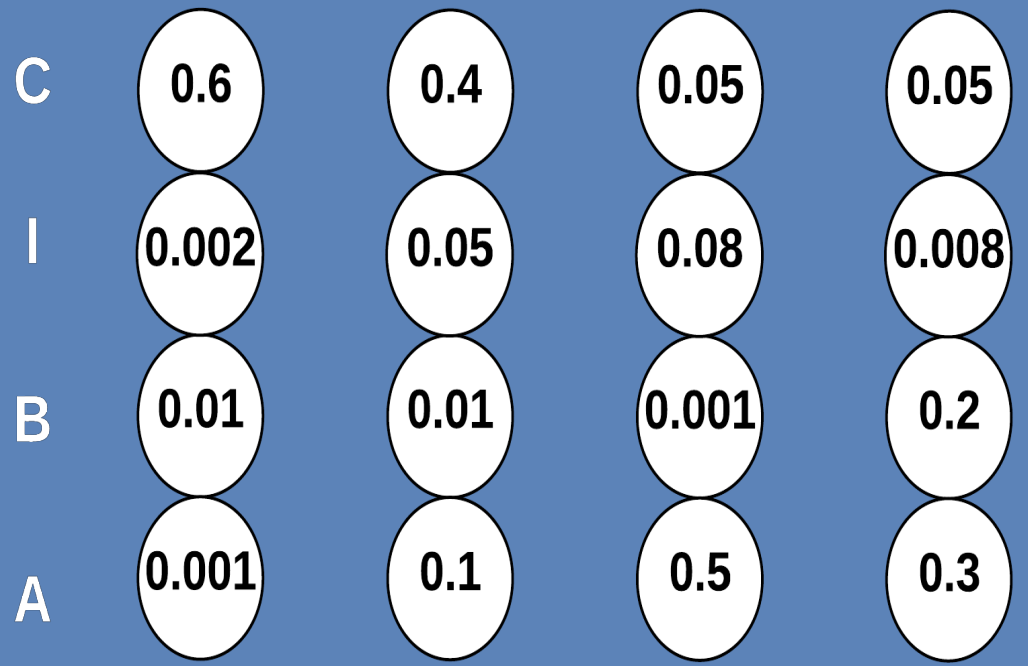
y_k^t the probability of character k at time t

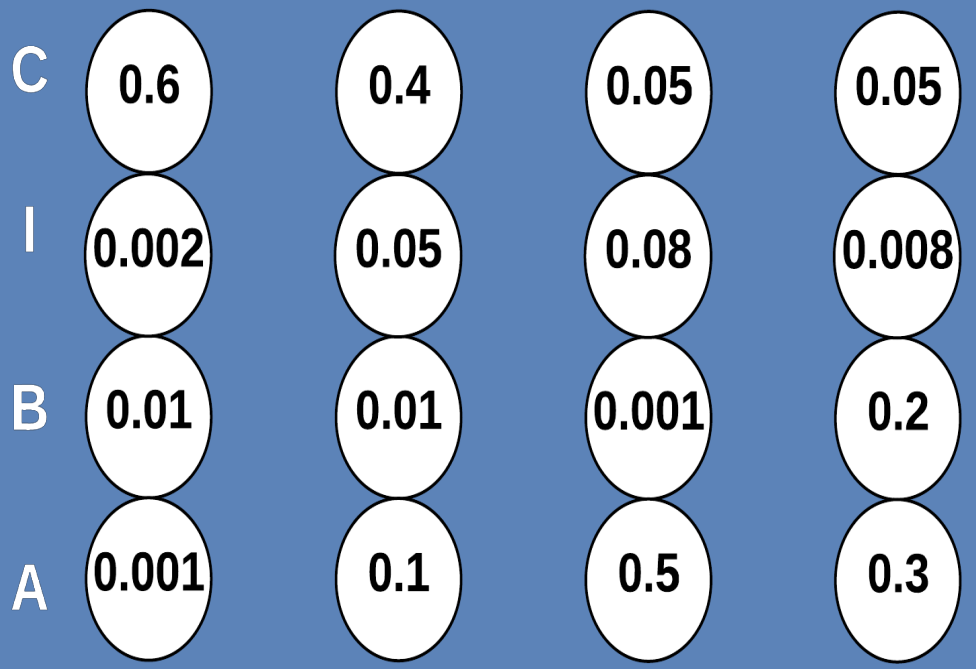
$Y = \{A, B, C, ..., Z, apostrophe, space, blank\}$



Connectionnist Temporal Classification

Connectionist Temporal Classification

- Each output dimension is a **node**
- A **path** is a sequence of nodes
- Probability of a path is the product of the probability of the nodes (independence of time steps)

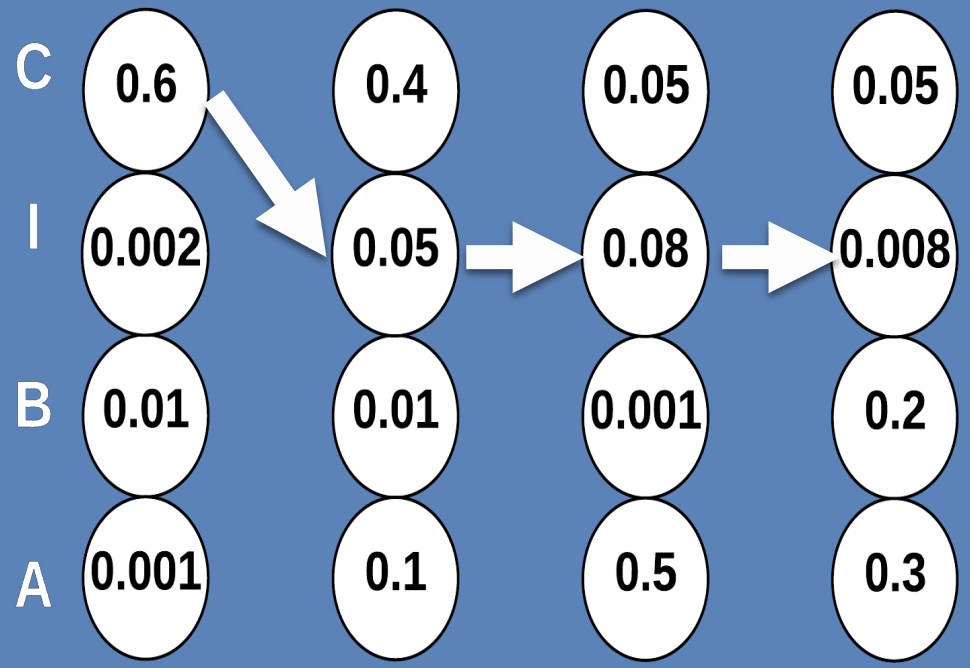


Connectionnist Temporal Classification

Connectionist Temporal Classification

$\pi = \pi_1, .., \pi_T$ a path in the graph

$$p(\pi|x) = \prod_{t=1}^{T} y^t_{\pi_t}, \forall \pi \in L^T$$



Probability(CIII) = 0.6*0.05*0.08*0.008 = 0.00000

Connectionnist Temporal Classification

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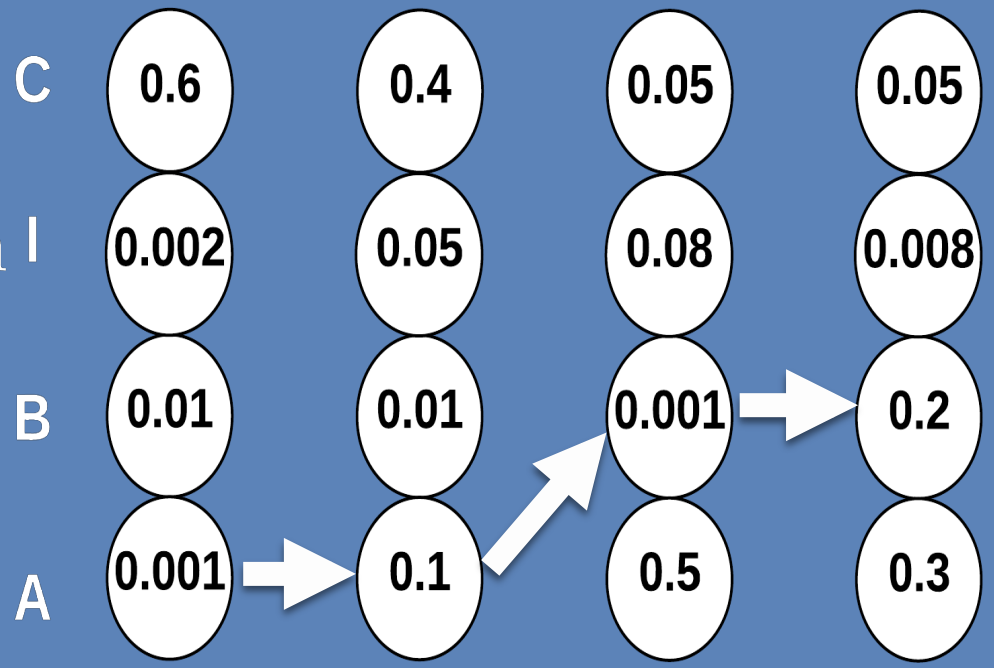


Probability(AABB) = 0.001*0.1*0.001*0.2 = 0.0000000

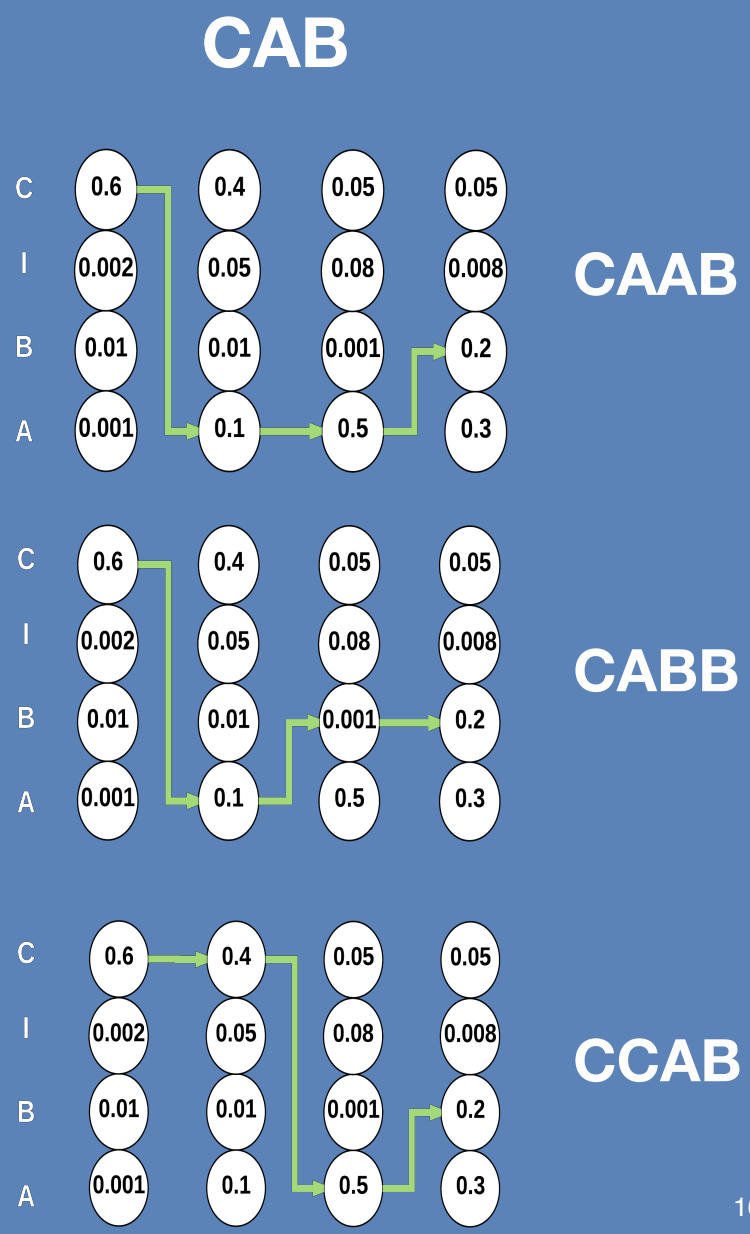
Connectionnist Temporal Classification

Training criterion

- Loss function:

$$-\sum_{\pi \in \text{Valid paths}} P(\pi|x)$$

- Maximize the valid paths
- Nothing for the other paths
- Train the entire network with backpropagation



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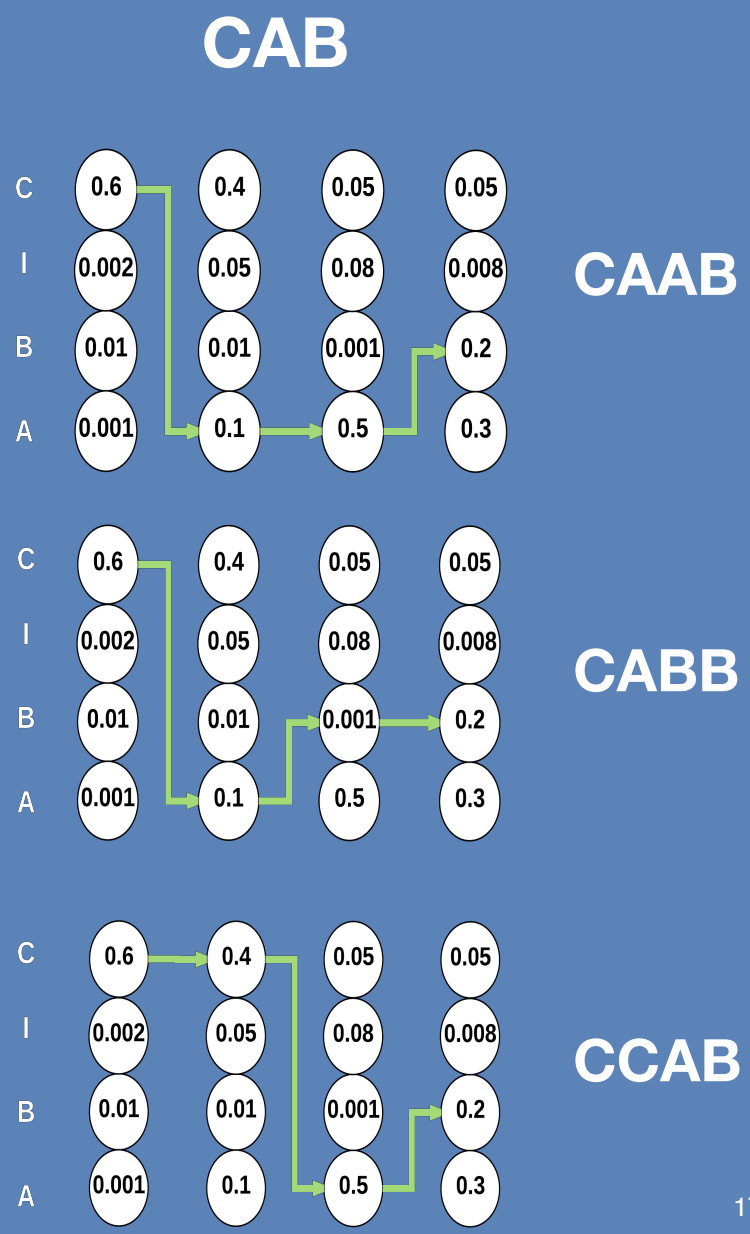
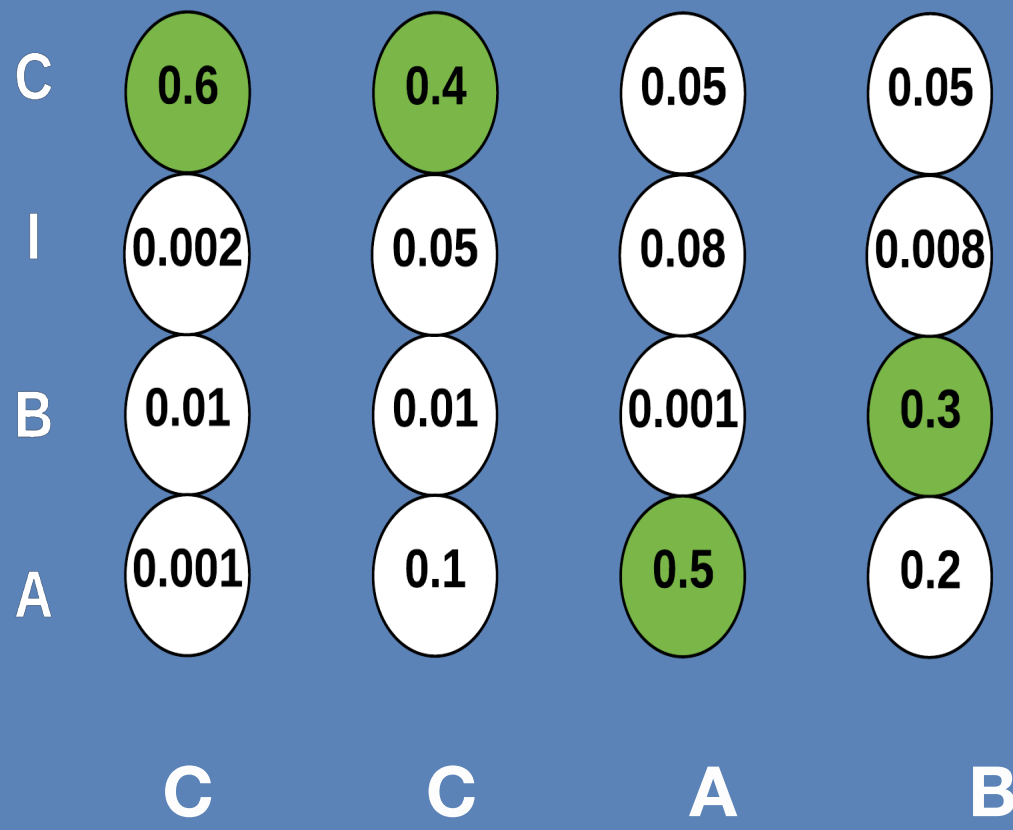


Connectionnist Temporal Classification

Decoding

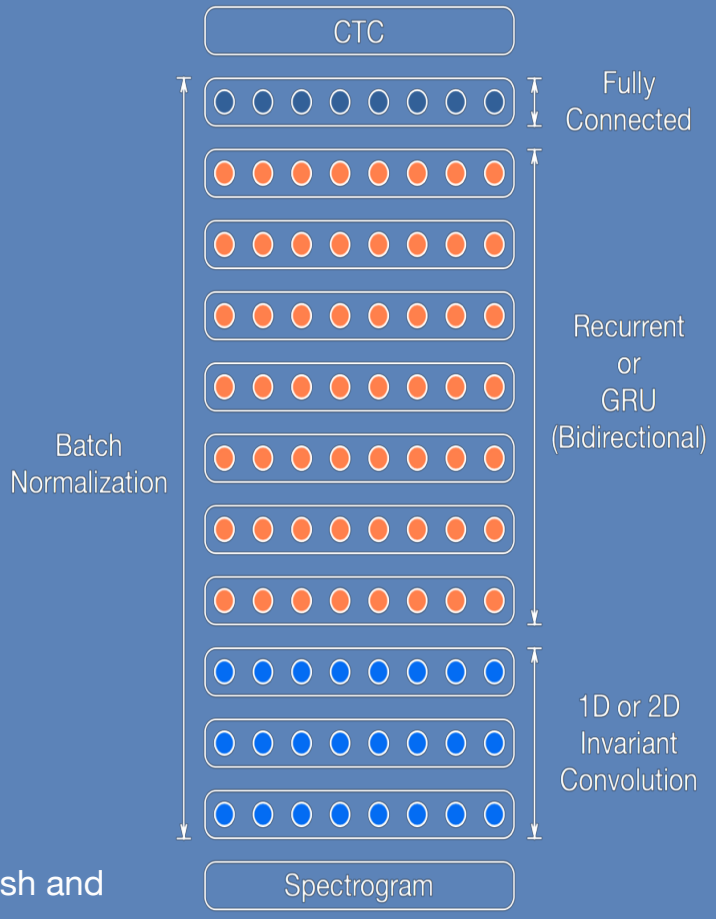
- The basic decoding is just to take the most likely character at each step
- It can incorporate a language model by adding the probability of words



Connectionnist Temporal Classification

Deep Speech 2

- Baidu system
- Combines convolutions on spectrograms, bi-directional RNN and CTC
- 100m parameters (best models)
- 16 GPUs (50TFlops)
- 3 to 5 days of training
- No speaker normalization (enough data to learn invariances!)



« Deep Speech 2: End-to-End Speech Recognition in English and Mandarin », Almodei et al.

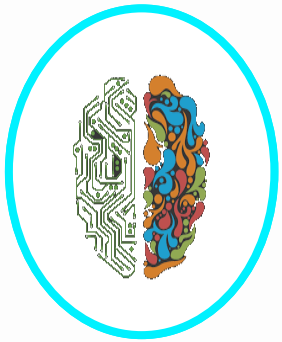
Connectionnist Temporal Classification

Current state-of-the-art

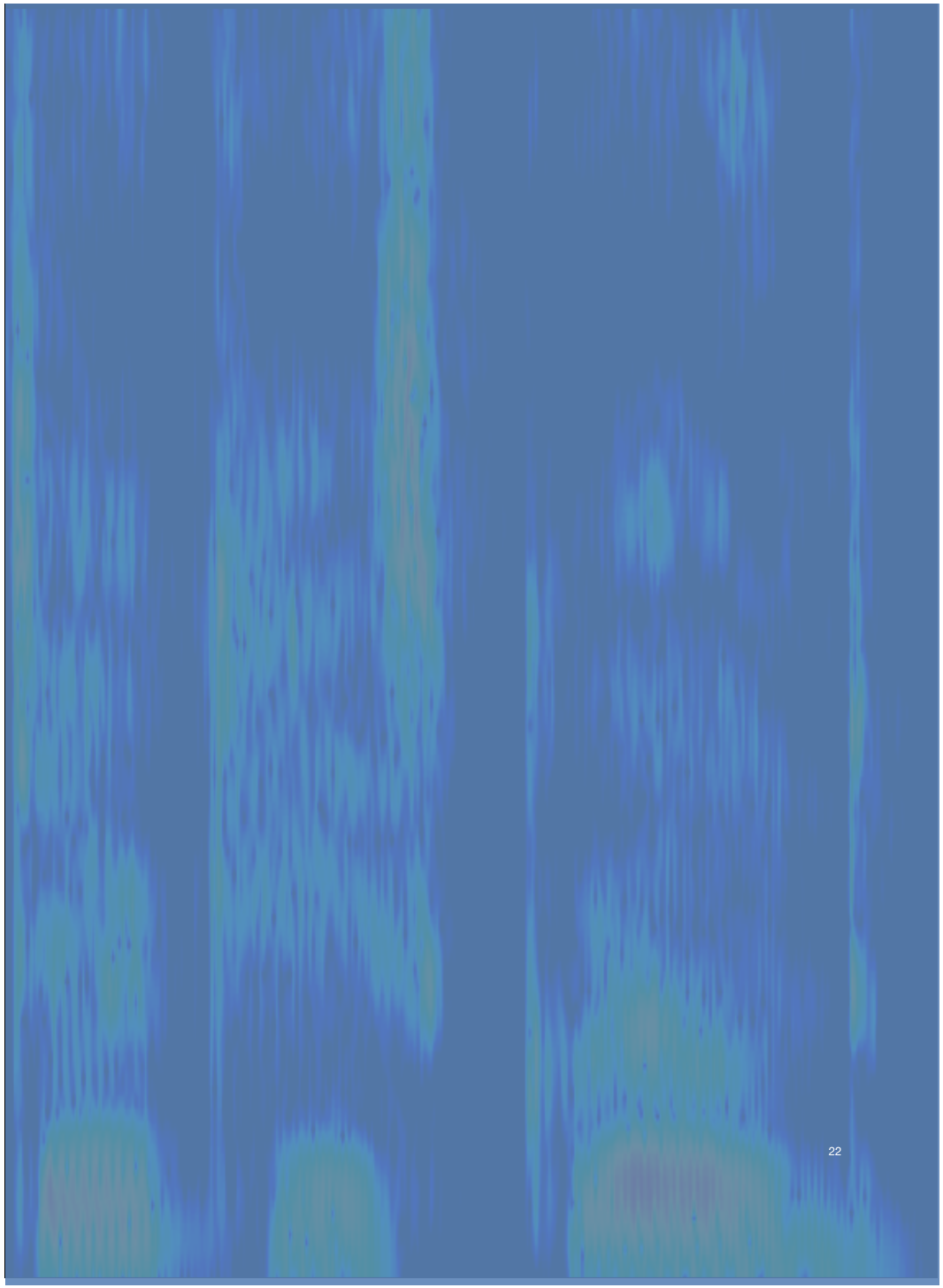
- The measure of Performance in speech recognition is called WER (Word Error Rate): how many words the system failed to recognize (in %) –> **the lower the better**
- Best systems are now on par with humans on conversational speech in English (~11% WER)

Resources

- Kaldi: http://kaldi-asr.org/
- Wav2letter (Torch): https://github.com/facebookresearch/wav2letter

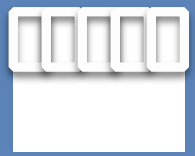


Neural Language models



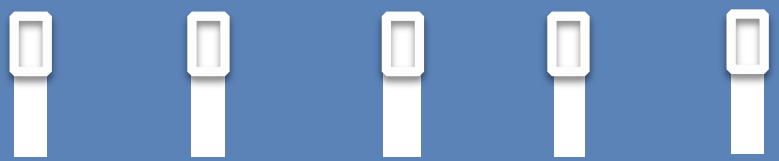
Neural Language Models

Recurrent acoustic model



Neural Language Models

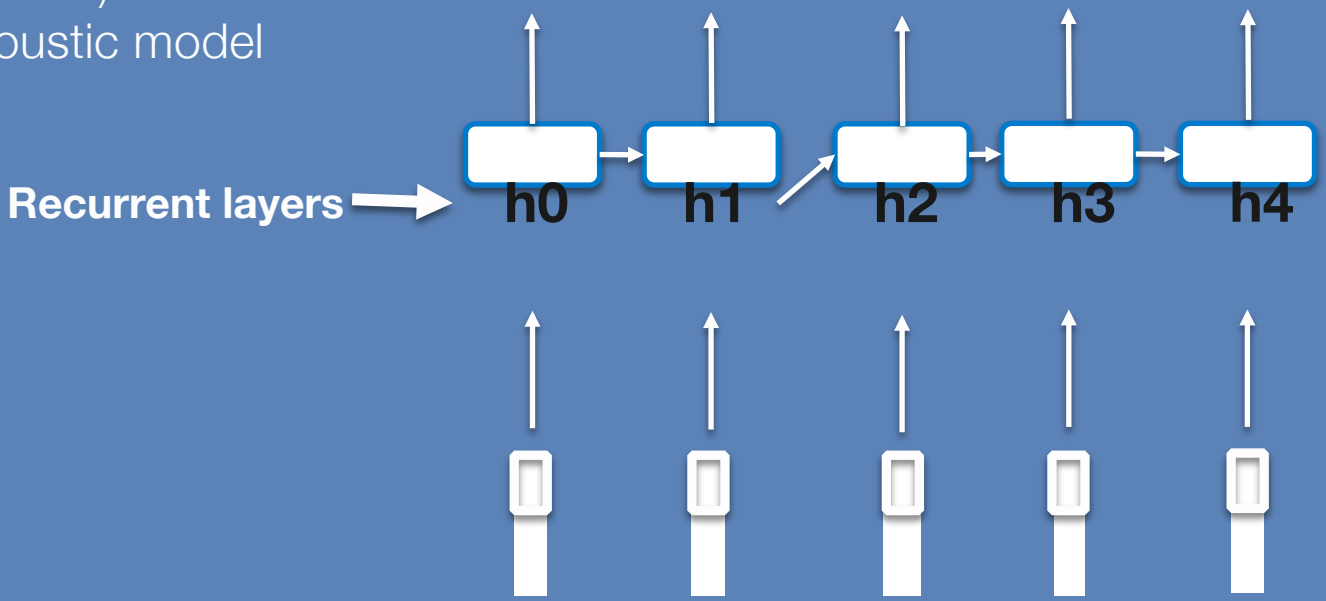
Recurrent acoustic model



Neural Language Models

Recurrent acoustic model

- Recurrent Neural Network used to output the distributions step by step
- Exploits the dependencies along the sequence (compensates for CTC)
- Most standard acoustic model in the past years



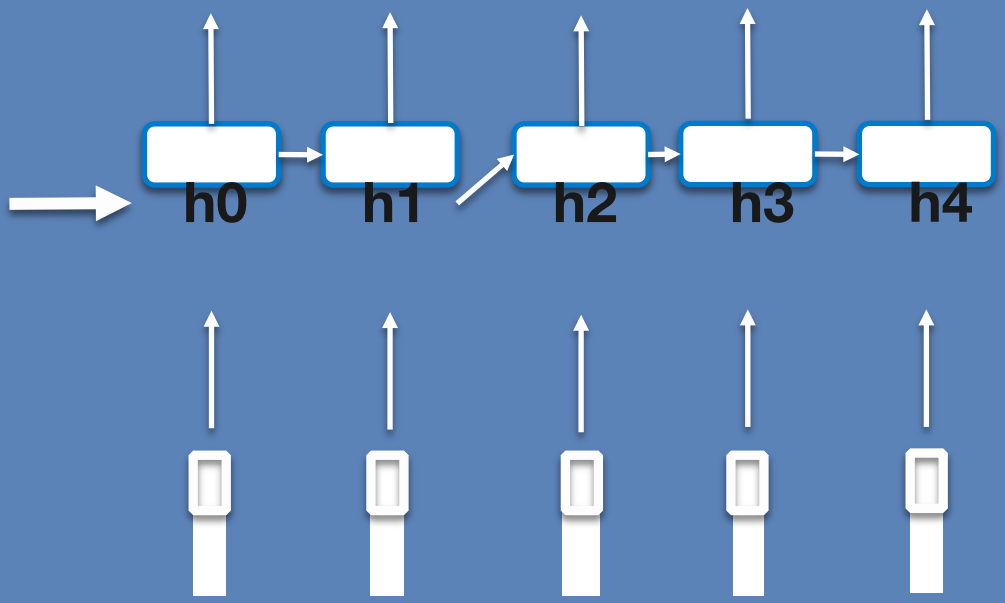
Neural Language Models

Recurrent acoustic model

$$h_0 = \tanh(W_x x_0)$$

$$h_t = tanh(W_x x_t + W_h h_{t-1} + b_h) \text{ for } t > 0$$

$$y^t = Softmax(W_{hy} h_t + b_y)$$



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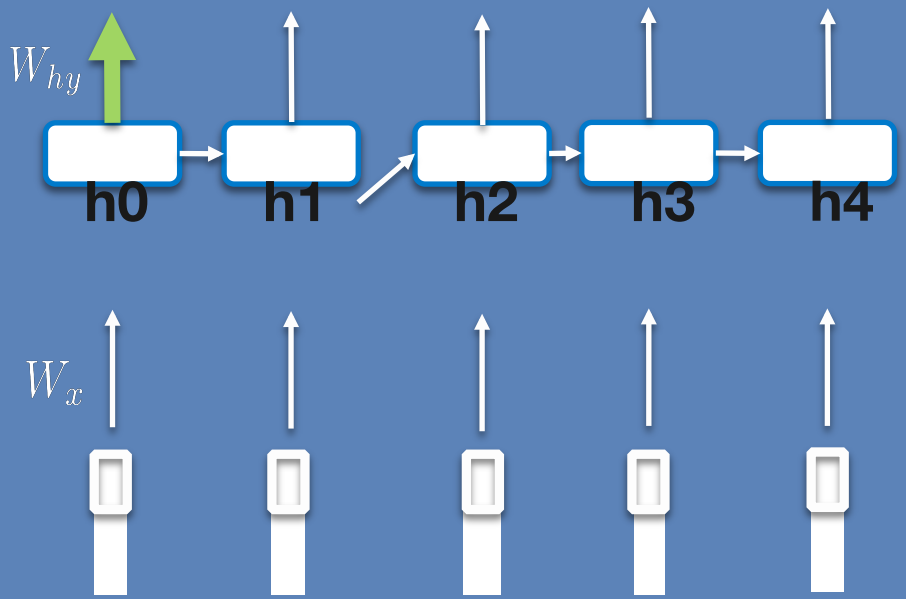
$P(y^0|x_0)$

A 0.6
B 0.002
C 0.01
D 0.001
...
Z 0.04



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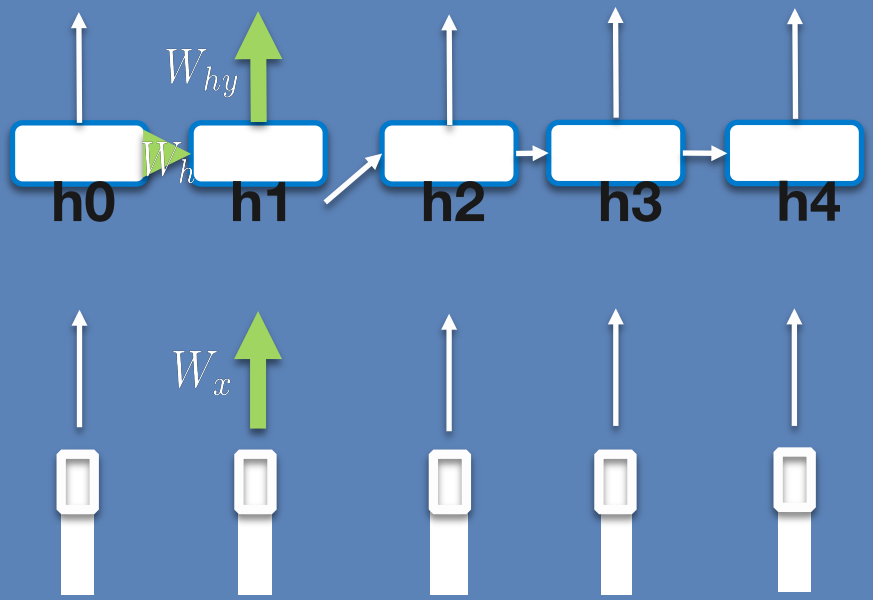
$P(y^1|x_1, h_0)$

A 0.6
B 0.002
C 0.01
D 0.001
…
Z 0.04



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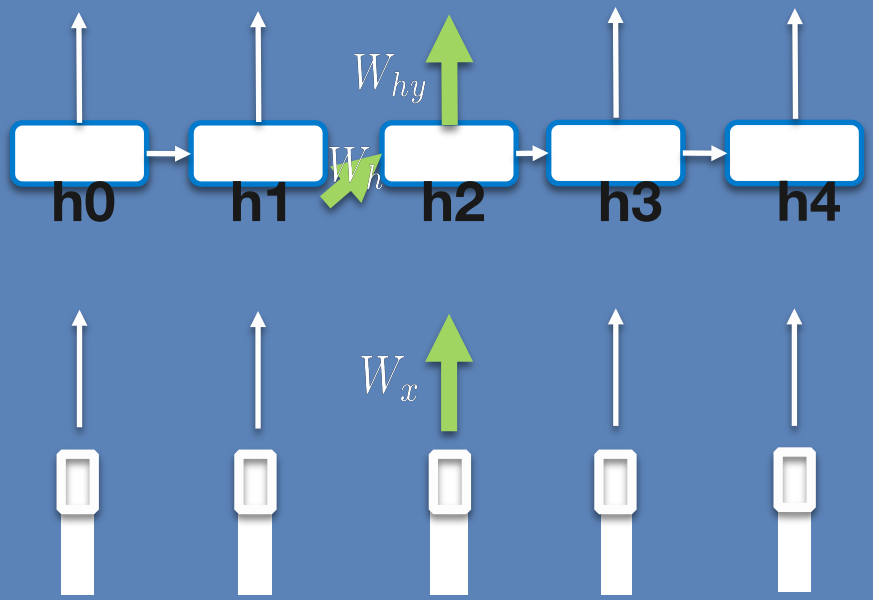
$$y^t = Softmax(W_{hy} h_t + b_y)$$

$P(y^2|x_2, h_1)$

A 0.6
B 0.002
C 0.01
D 0.001
...
Z 0.04



Neural Language Models

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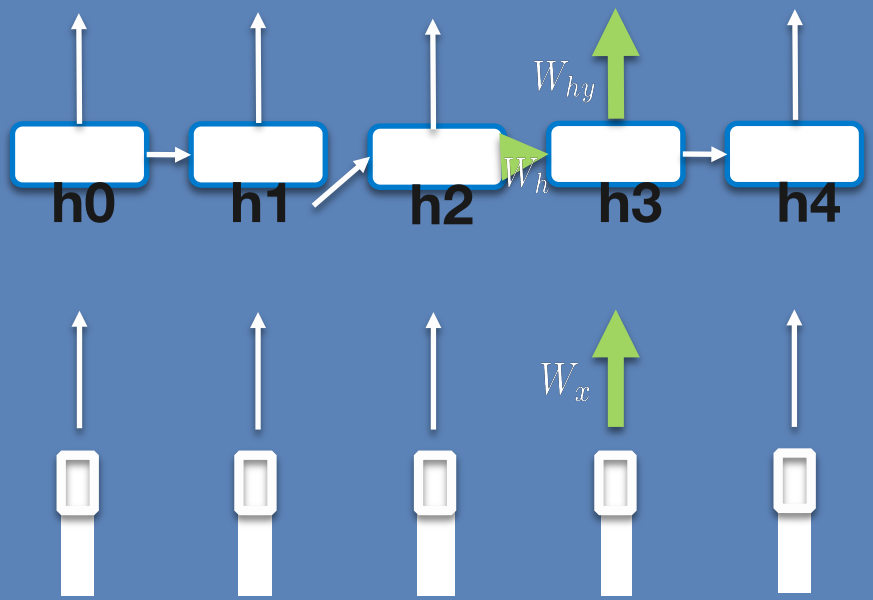
$$y^t = Softmax(W_{hy} h_t + b_y)$$

$P(y^3|x_3, h_2)$

A 0.6
B 0.002
C 0.01
D 0.001
...
Z 0.04



Neural Language Models

Recurrent acoustic model

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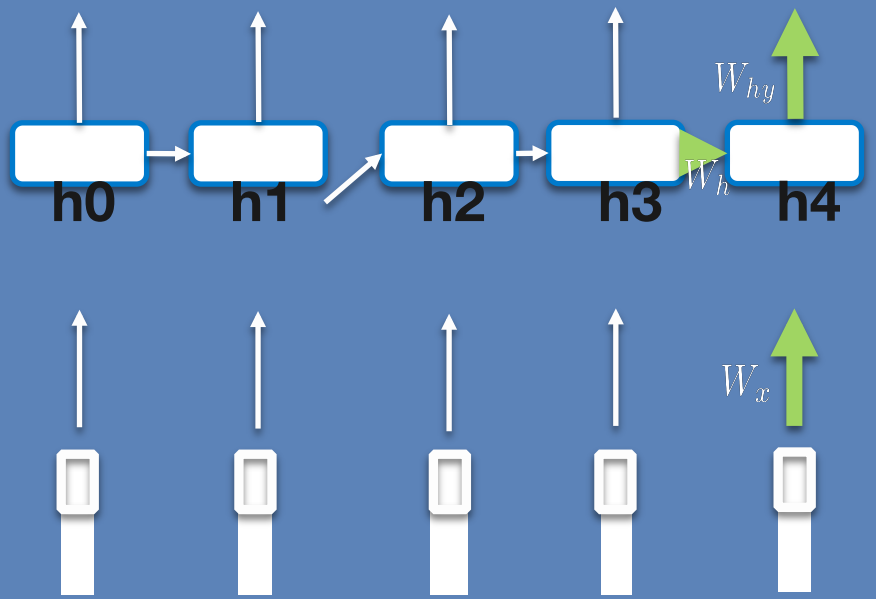
$$h_t = tanh(W_x x_t + W_h h_{t-1} + b_h) \text{ for } t > 0$$

$$y^t = Softmax(W_{hy} h_t + b_y)$$

$P(y^4|x_4, h_3)$

A 0.6
B 0.002
C 0.01
D 0.001
...
Z 0.04



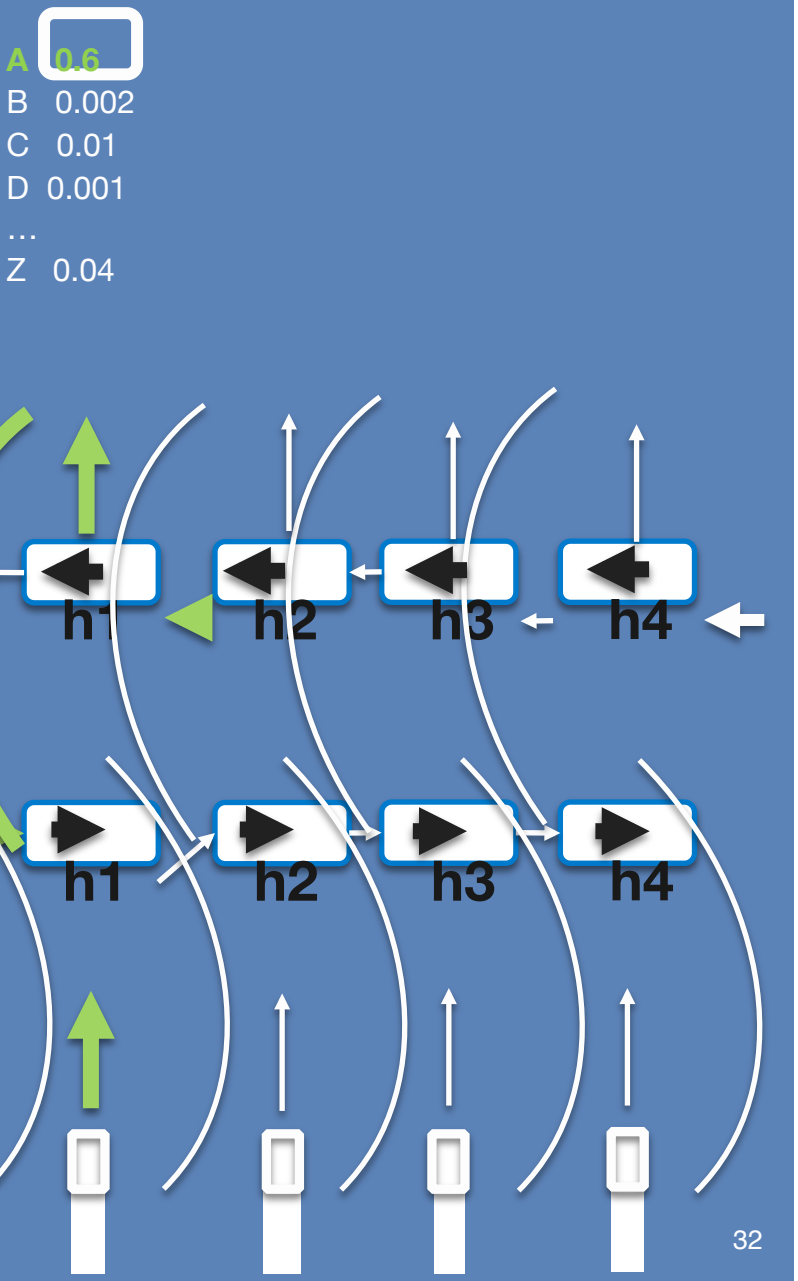
Neural Language Models

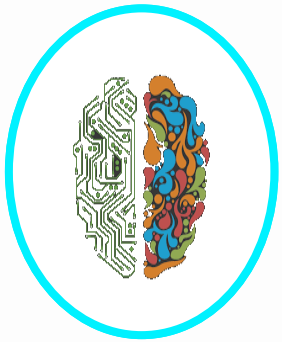
Bi-directional RNN

$$\overrightarrow{h}_0 = tanh(W_x x_0)$$
$$\overleftarrow{h}_T = tanh(W_x x_T)$$

$$\overleftarrow{h}_t = tanh(W_x x_t + W_{\overleftarrow{h}} \overleftarrow{h}_{t-1} + b_{\overleftarrow{h}}) \text{ for } t < T$$
$$\overrightarrow{h}_t = tanh(W_x x_t + W_{\overrightarrow{h}} \overrightarrow{h}_{t-1} + b_{\overrightarrow{h}}) \text{ for } t > 0$$

$$y^t = Softmax(W_{\overrightarrow{h}y} \overrightarrow{h}_t + W_{\overleftarrow{h}y} \overleftarrow{h}_t + b_y)$$



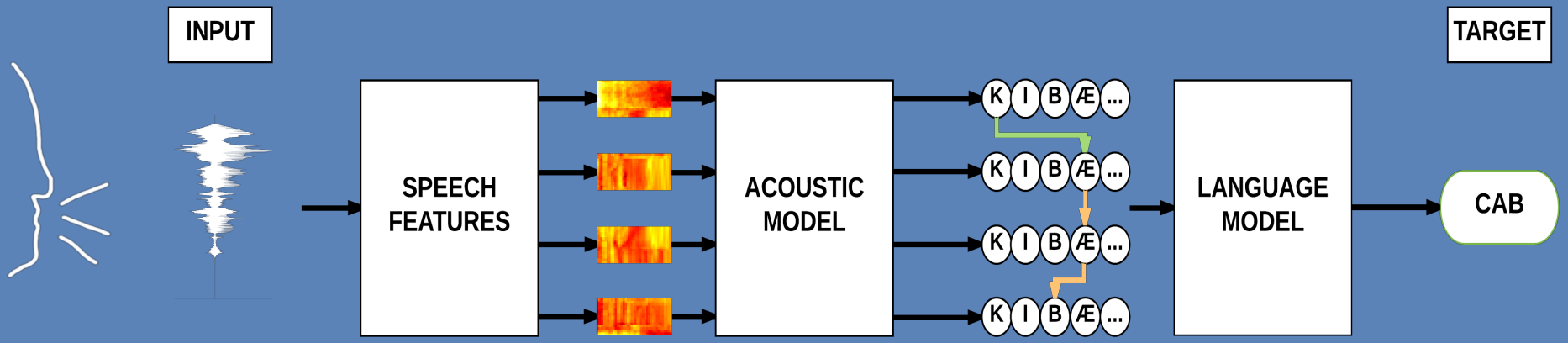


New developments

- Recognition from raw waveforms

Learning from raw waveform

Is this « end-to-end » learning?



Learning from raw waveform

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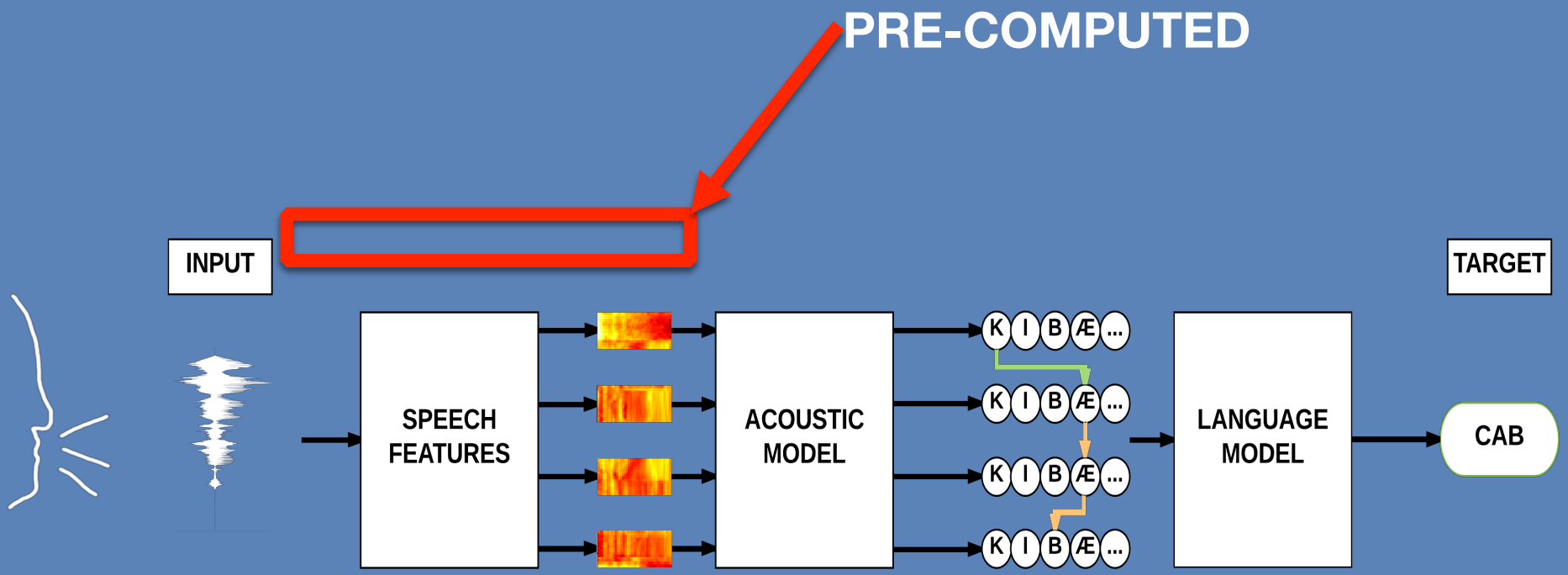
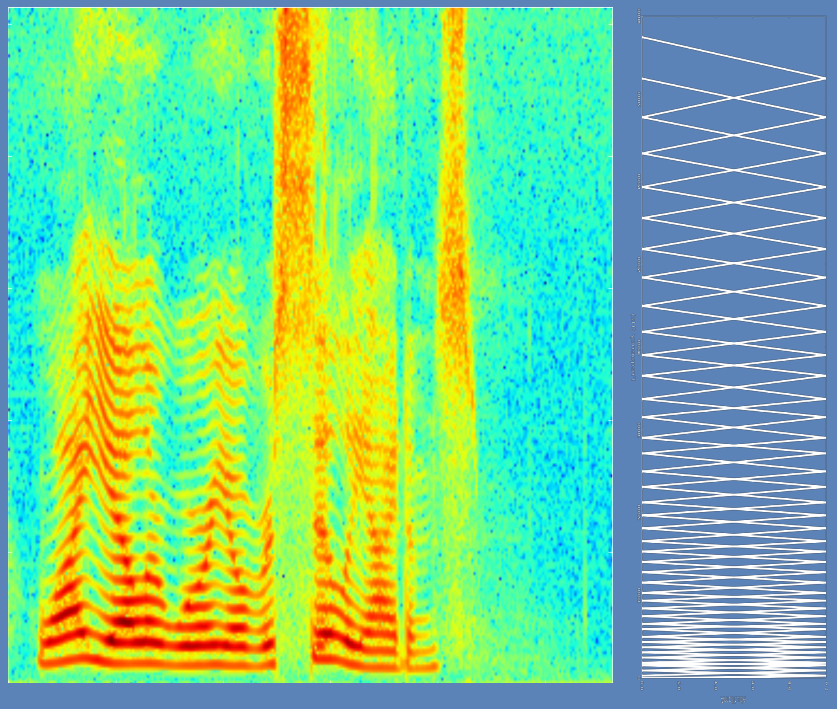


Learning from raw waveform

Can we learn the mel-filterbanks?

$$Melfbank_j(k) = \sum_{\omega=0}^{256} Spectrogram(k,\omega) Melfilter_j(\omega)$$

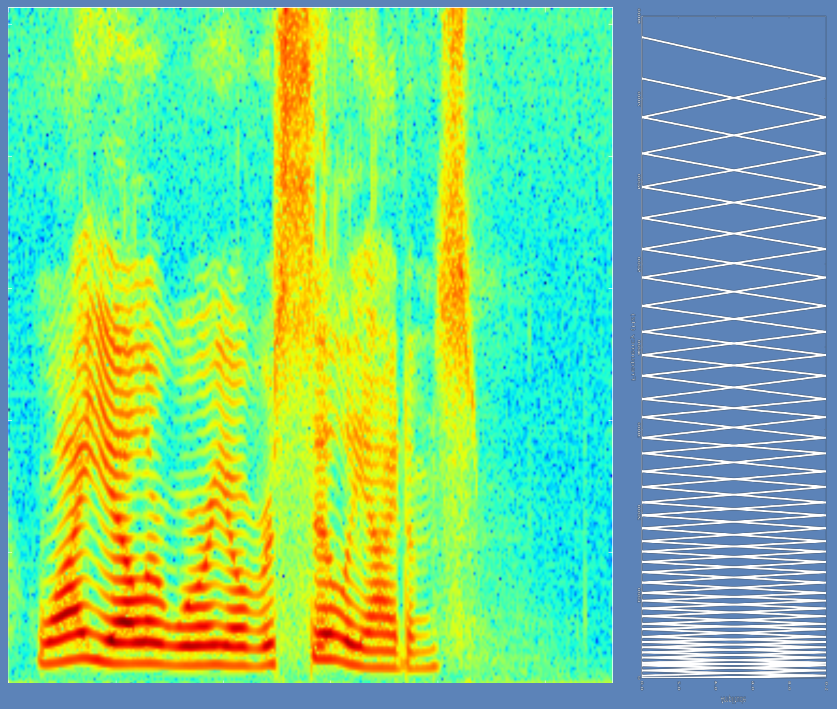


Learning from raw waveform

Can we learn the mel-filterbanks?

- This can be computed by a convolution over the frequency axis

« Learning Filter Banks Within a Deep Neural Network Framework», Sainath et al.



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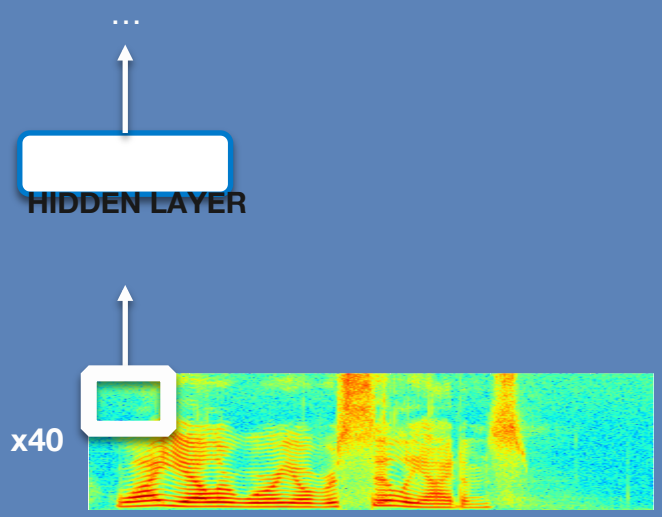

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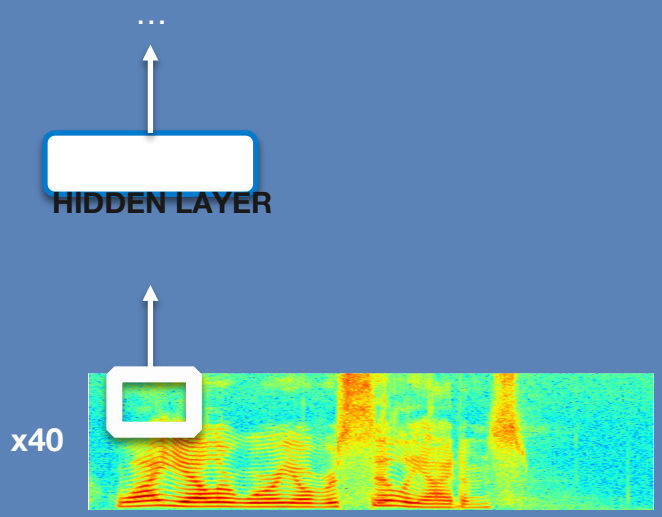
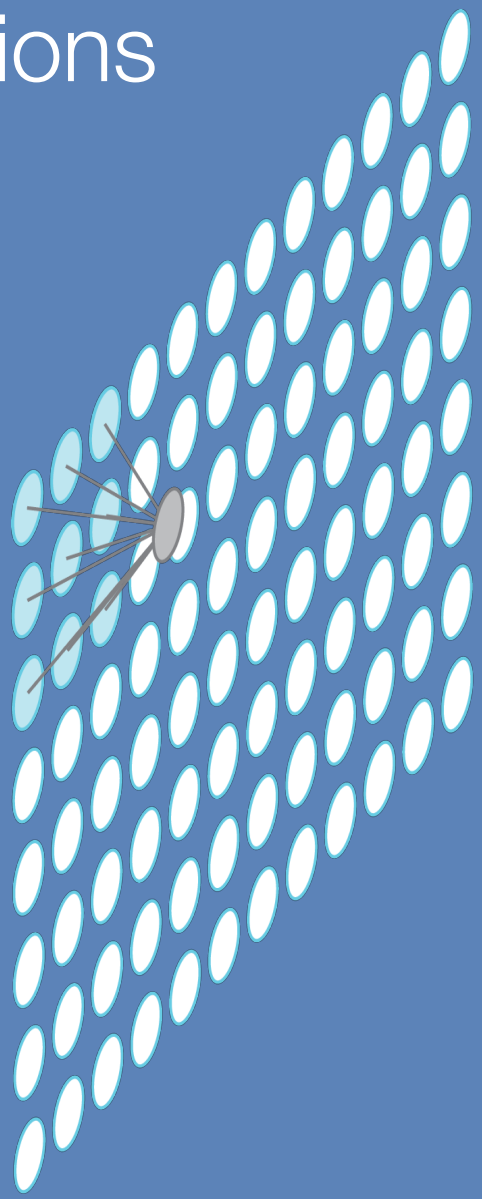
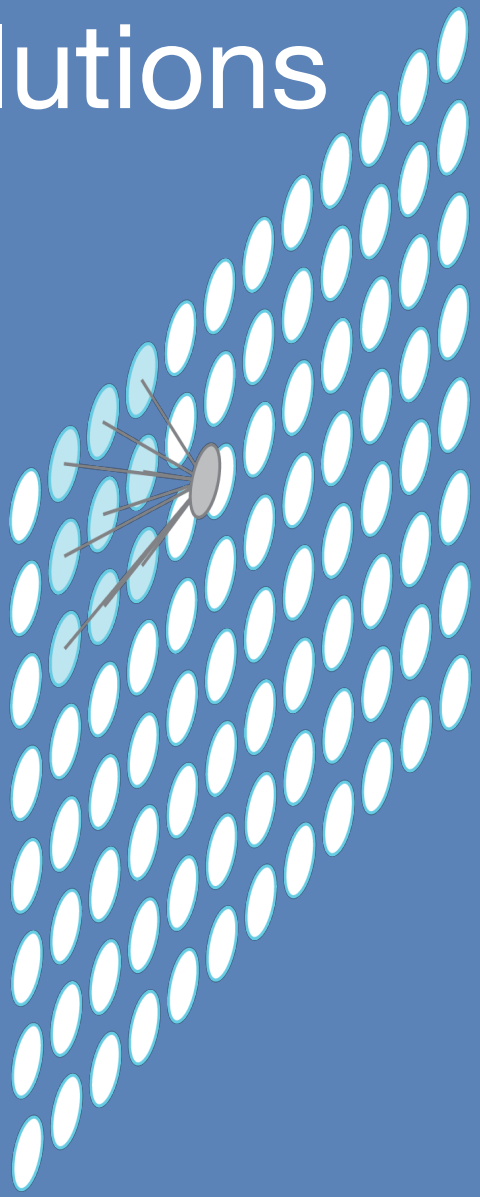


- 2-D Convolutions



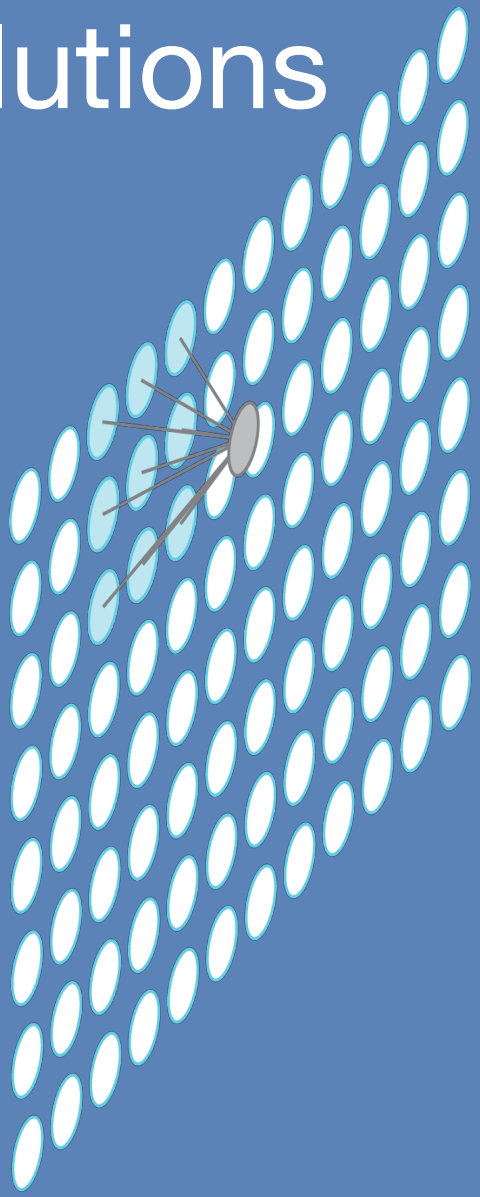
Kernel size : 1 x 3 x 3
Number of kernels : 1

2-D Convolutions



Kernel size : 1 x 3 x 3
Number of kernels : 1

2-D Convolutions



Kernel size : 1 x 3 x 3
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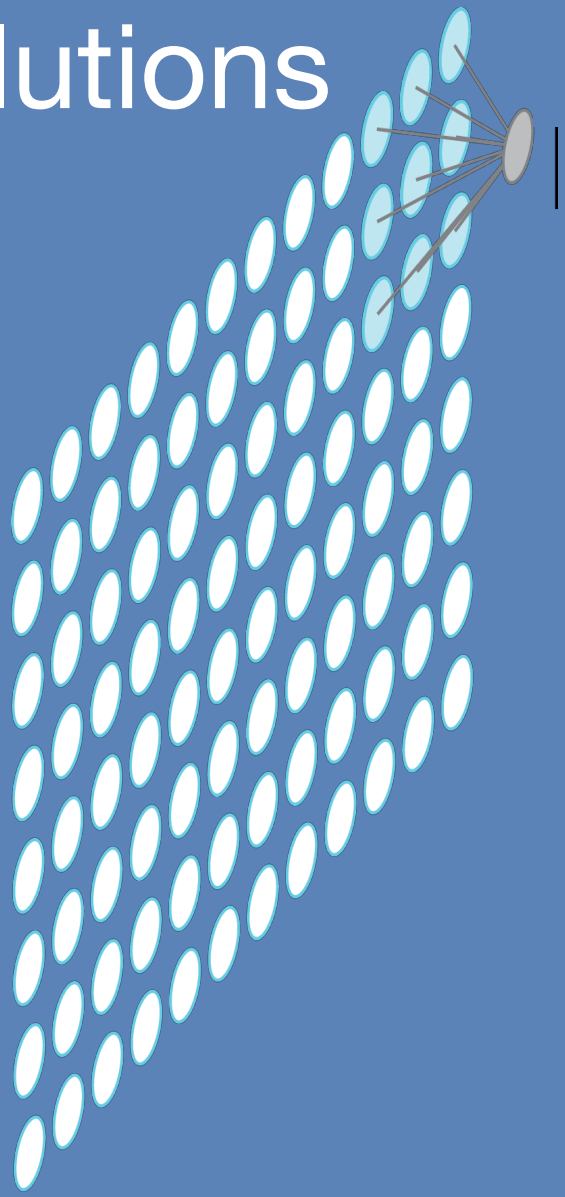
2-D Convolutions



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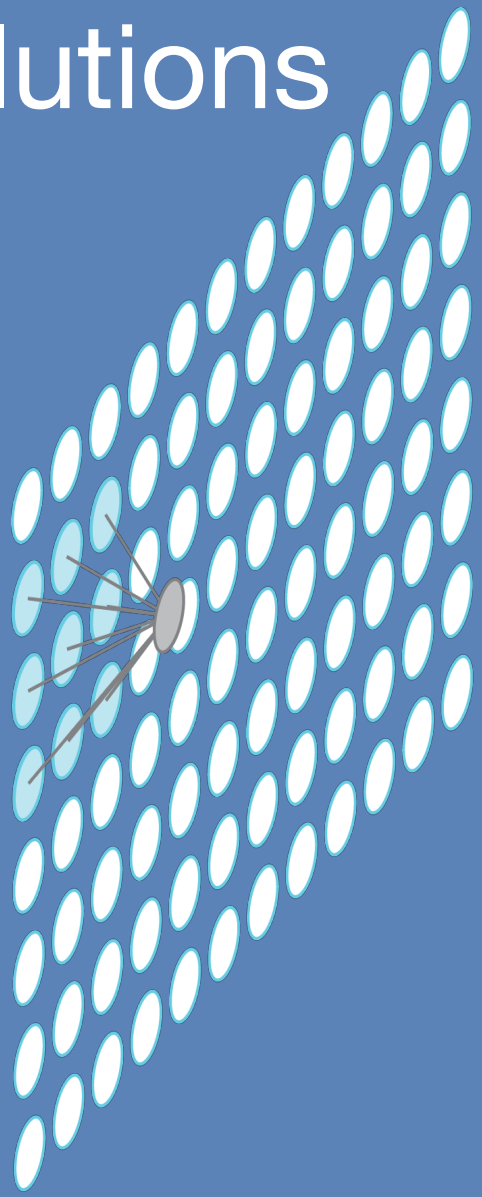
2-D Convolutions



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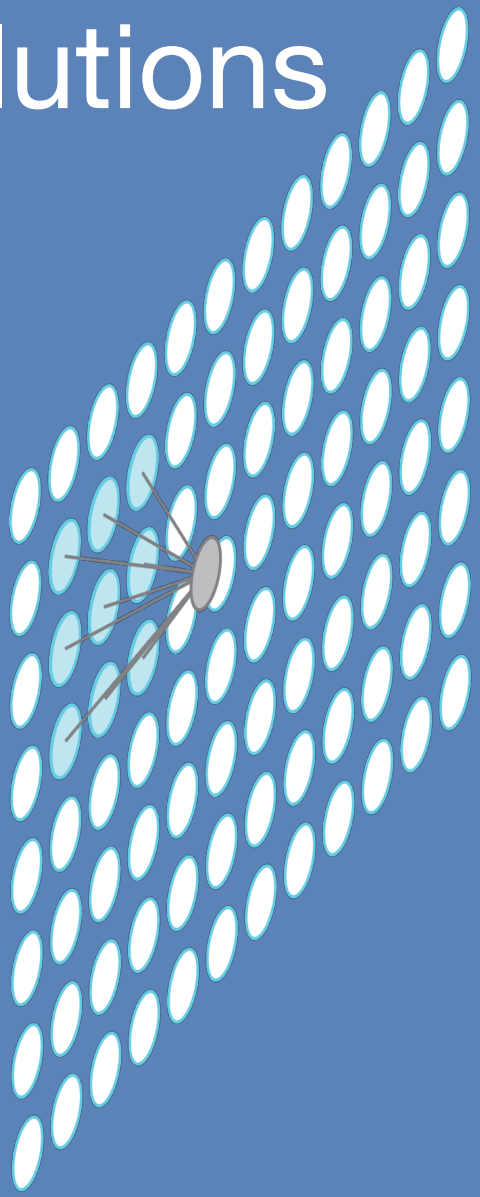
2-D Convolutions



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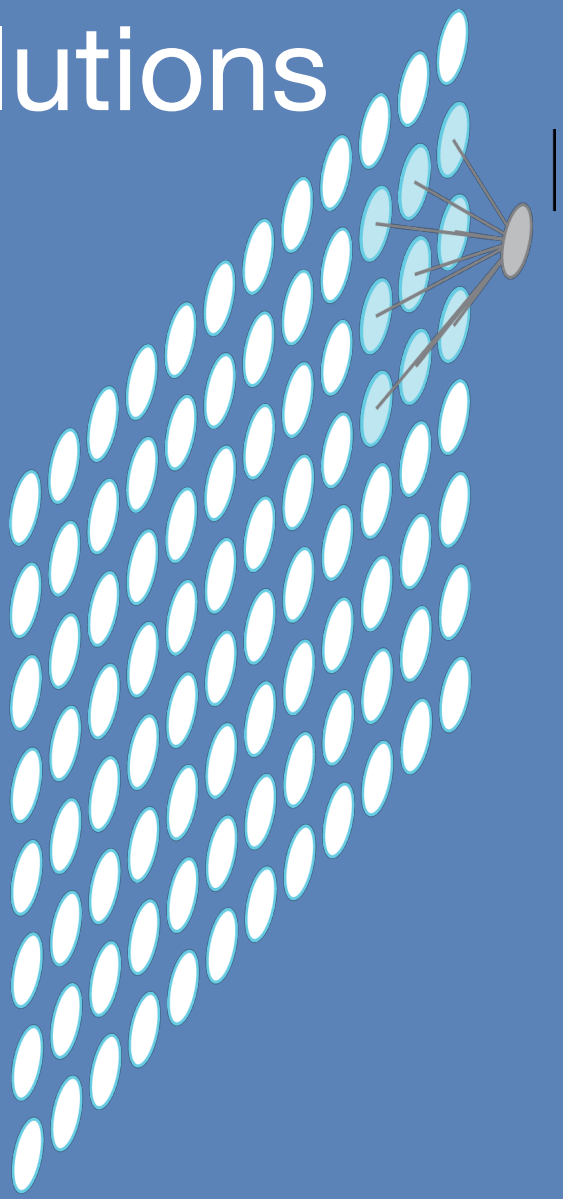
2-D Convolutions



Kernel size : 1 x 3 x 3

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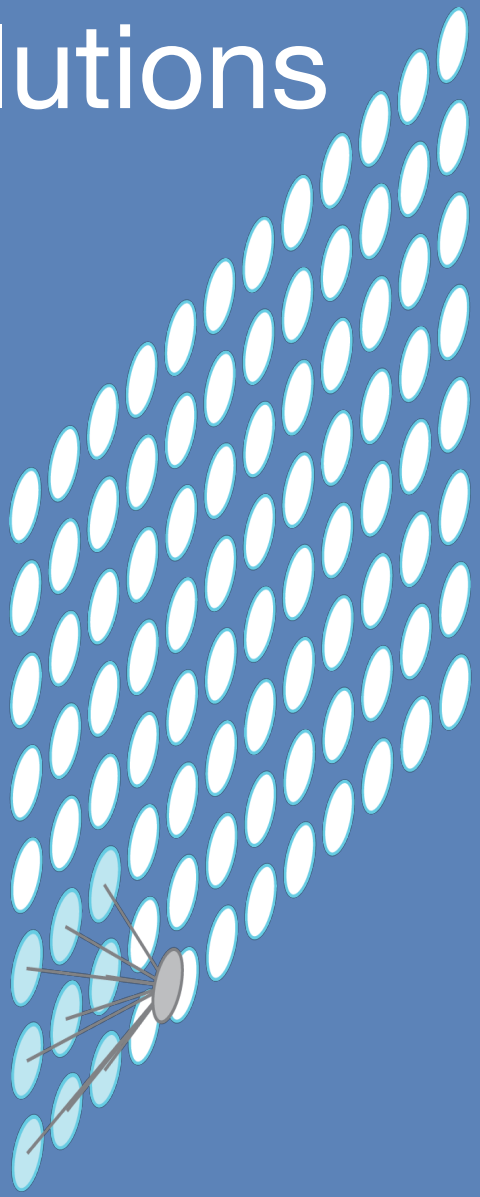
2-D Convolutions



Kernel size : 1 x 3 x 3
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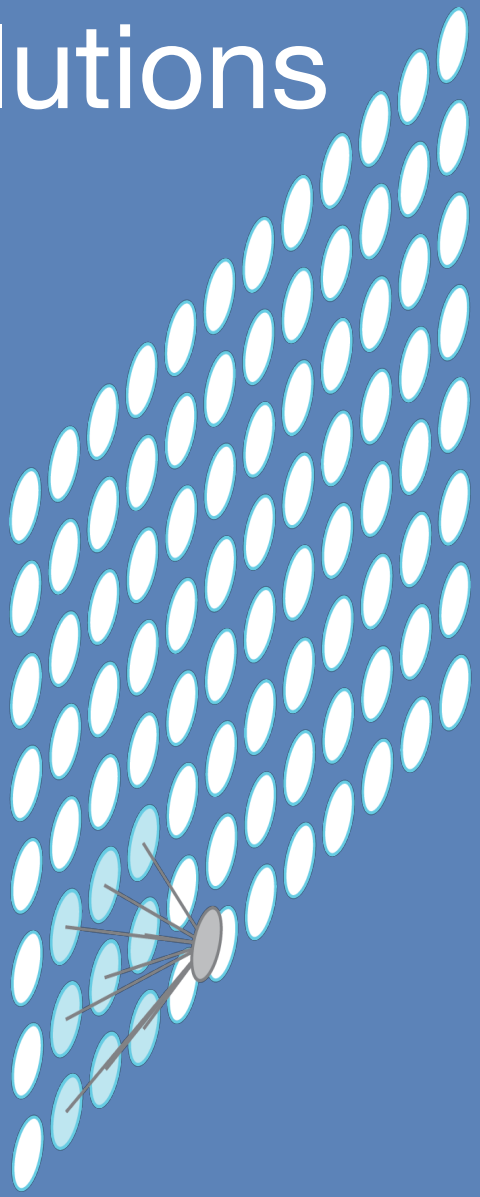
2-D Convolutions



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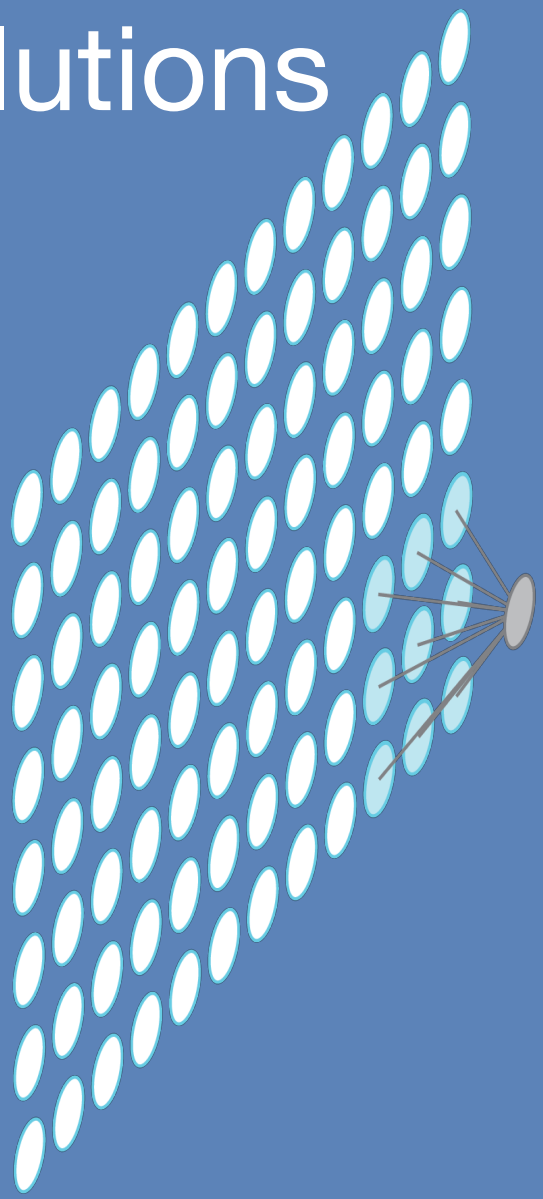
2-D Convolutions

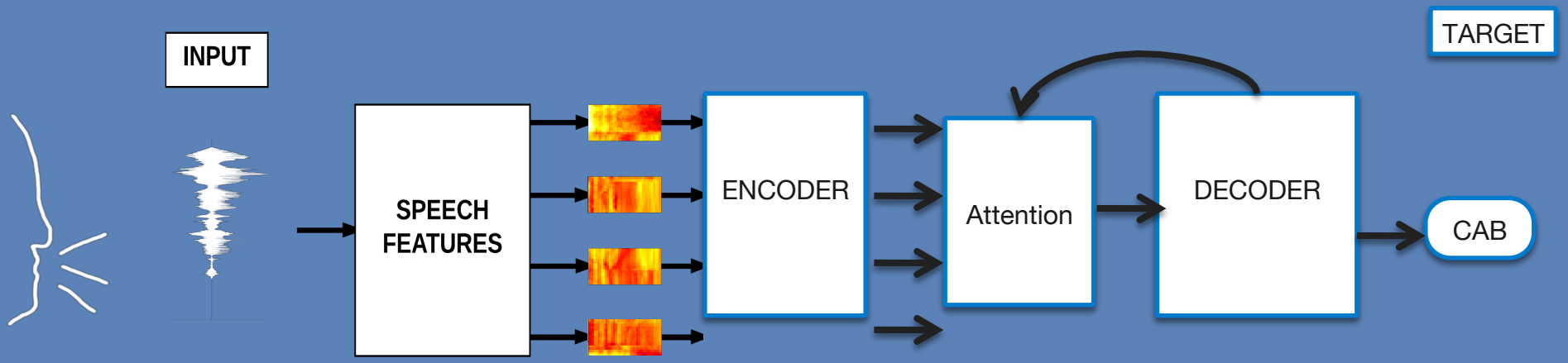


Kernel size : 1 x 3 x 3
Number of kernels : 1

Zeghidour et al (2018). Learning from raw waveform

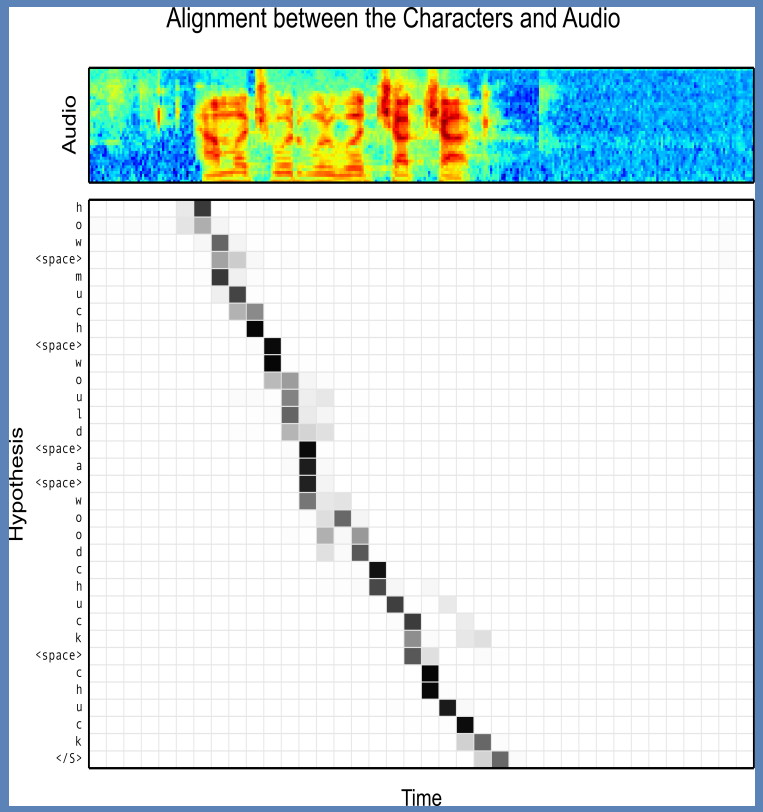
Sequence to Sequence

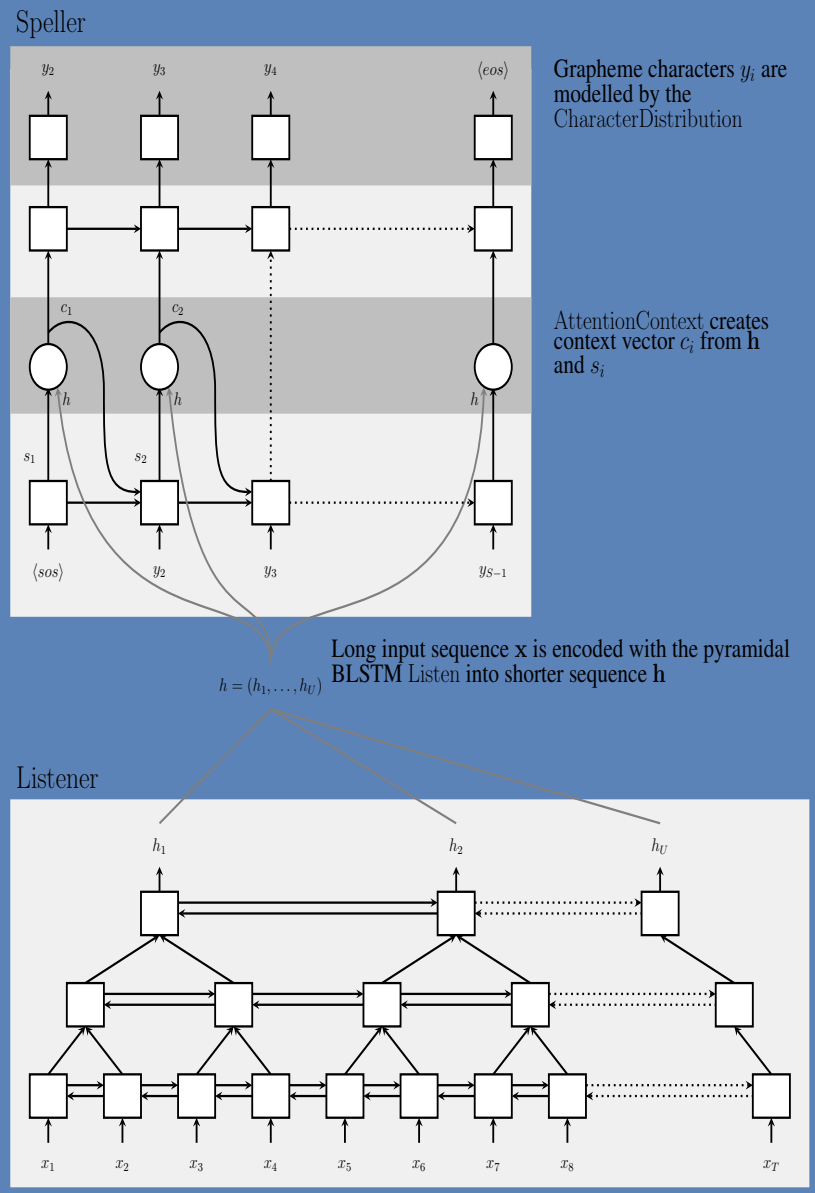
Sequence to sequence



Sequence to Sequence

Alignment via attention





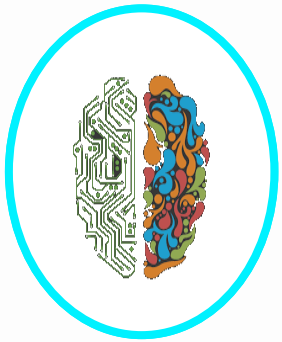
Listen, Attend and Spell (2015). Chan et al.

Sequence to Sequence

Improvements

- Word Pieces (instead of characters)
- Multiheads
- Optimizations
- 12K hours of speech

State of the art with Sequence to sequence models (2018). Chui et al.



Open problems

- Challenging types of speech
- Need of data

What about accented/noisy speech?

Accented Speech			
Test set	DS1	DS2	Human
VoxForge American-Canadian	15.01	7.55	4.85
VoxForge Commonwealth	28.46	13.56	8.15
VoxForge European	31.20	17.55	12.76
VoxForge Indian	45.35	22.44	22.15

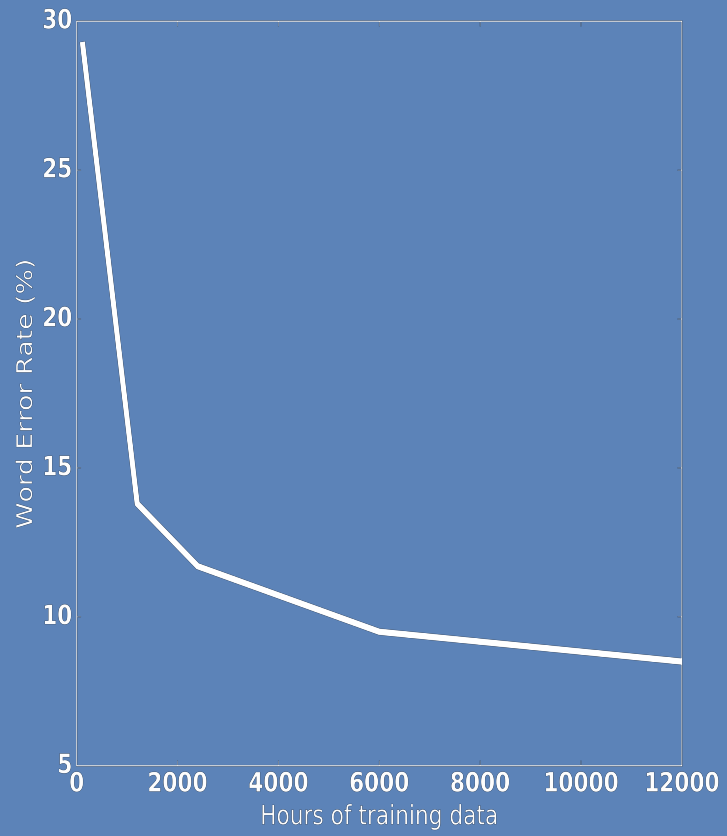
Word error rate of DeepSpeech 2 on accented speech

Noisy Speech			
Test set	DS1	DS2	Human
CHiME eval clean	6.30	3.34	3.46
CHiME eval real	67.94	21.79	11.84
CHiME eval sim	80.27	45.05	31.33

Word error rate of DeepSpeech 2 on noisy speech

Limitations of current approaches

How much data do we need?



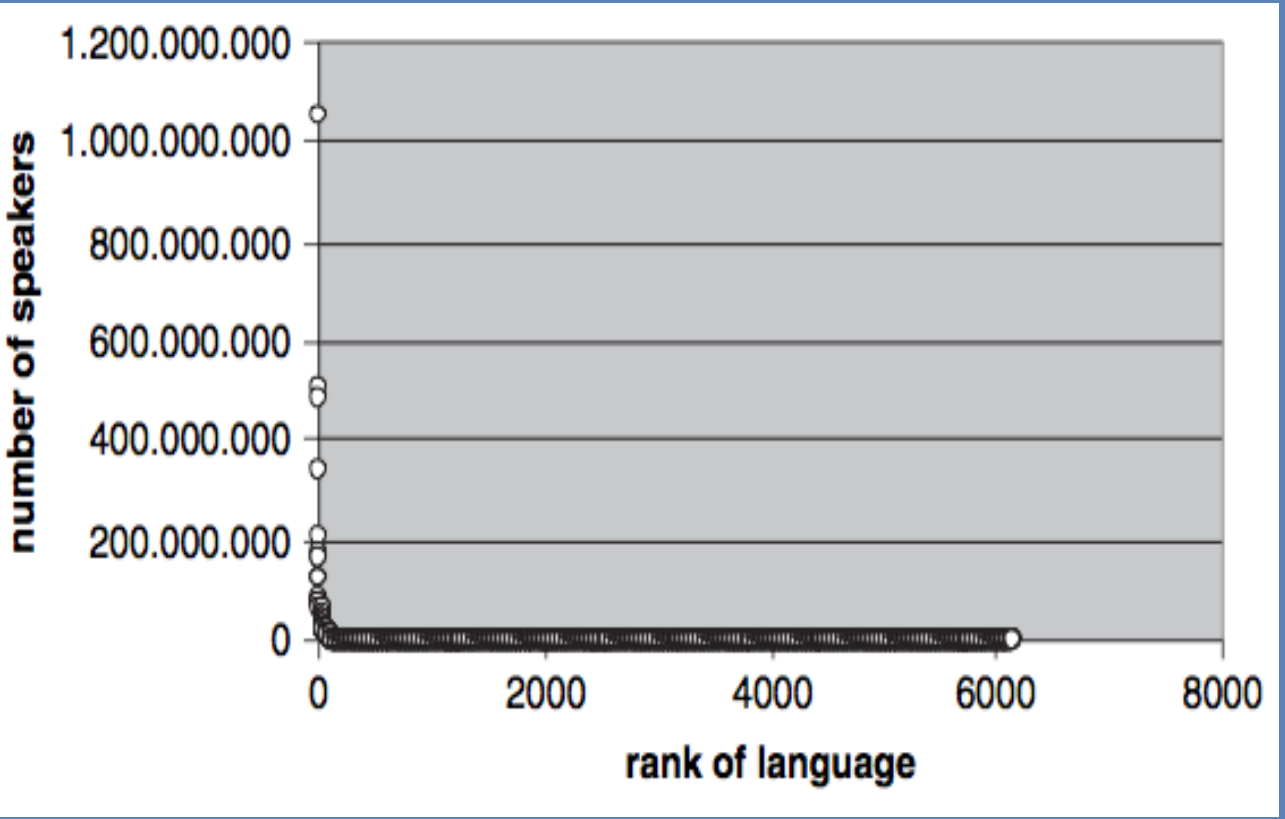
Limitations of current approaches

Challenges

- Low-resource languages
- Languages without standard orthography
  Half of the ~7000 languages in the world
- Evolving vocabulary, new categories of users, new accents

Limitations of current approaches

Low-resource languages



Limitations of current approaches

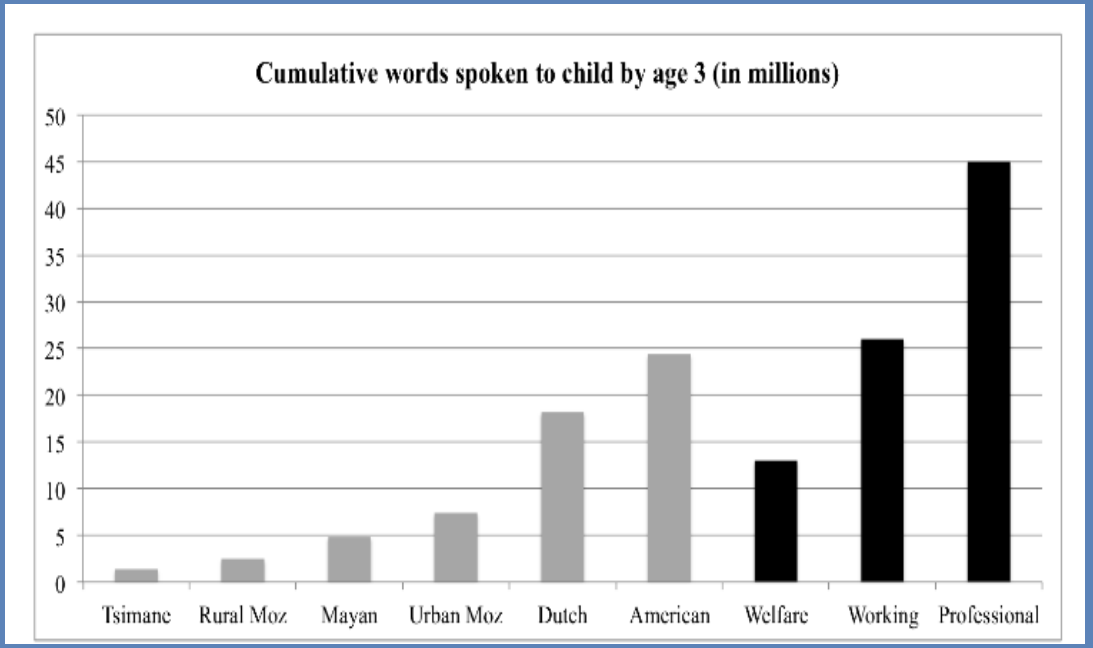
Efficiency of human learning

Deep Speech 2
12000h

...

- Small and varying quantity of data
- No annotations!
- Two speakers!
- We learn speech recognition, robustness to noise, quick adaptation to new accents

From Cristia et al. (2017) Child Development.



66 h/year **800 h/year** **1200 h/year**

Limitations of current approaches

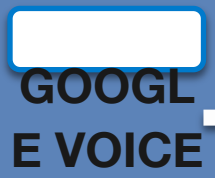
Adversarial examples

$$\tilde{x} = \underset{\tilde{x}:\|\tilde{x}-x\|_p \leq \epsilon}{\operatorname{argmax}} \ \ell\big(g_\theta(\tilde{x}), y\big)$$

Perturbation minimal in input space (pixels of an image, waveform of speech) but maximal for the classifier

Limitations of current approaches

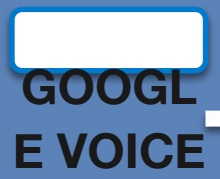
Adversarial examples



"The bearing was graceful an animated she let her son by the hand and before he walks two maids with wax lights and silver candlesticks."

Limitations of current approaches

Adversarial examples

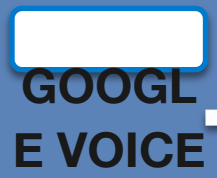


"The bearing was graceful an animated she let her son by the hand and before he walks two maids with wax lights and silver candlesticks."

Add a bit of noise…

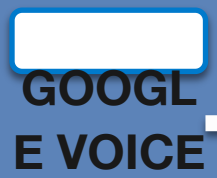
Limitations of current approaches

Adversarial examples



"The bearing was graceful an animated she let her son by the hand and before he walks two maids with wax lights and silver candlesticks."

Add a bit of noise…



"Mary was grateful then admitted she let her son before the walks to Mays would like slice furnace filter count six."

Limitations of current approaches

« DolphinAttack »: Inaudible attacks on ASR systems

- Researchers have managed to create voice commands that are carried by a high frequency signal (>20kHz)

- These commands are inaudible for humans, but the microphone of ASR systems retrieves the command

- Without anyone hearing they could:
  - Fool 16 speech recognition systems (Siri, Amazon Echo, Google Nexus, etc.)
  - Launching Facetime, calling desired numbers
  - Playing Music or opening the back door with Amazon Echo
  - Put smartphones in airplane mode
  - Manipulate the navigation system of an Audi

« DolphinAttack: Inaudible Voice Commands », Zhang et al.