ASR and Dynamic Programming



Automatic speech recognition

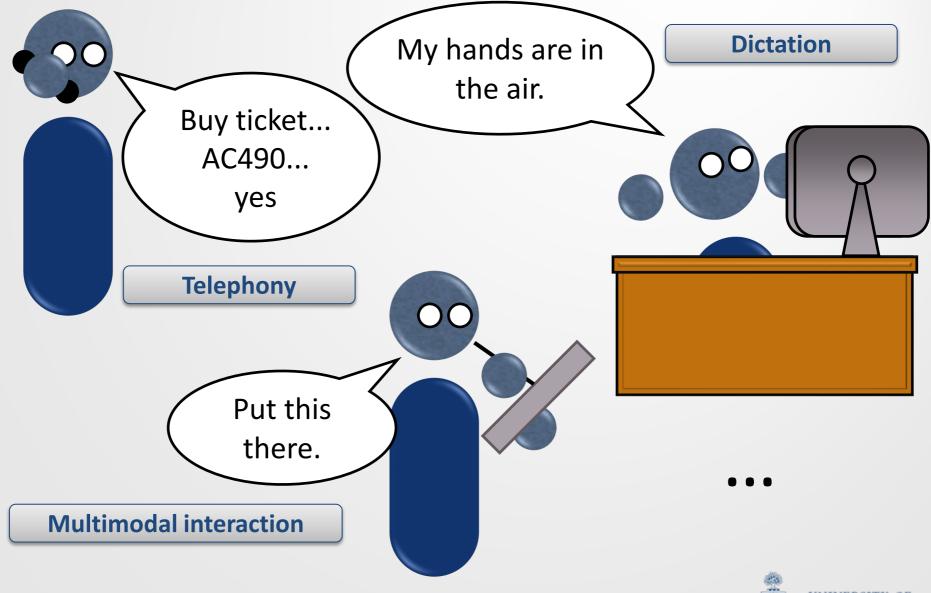
Given an utterance, recorded as a waveform...

 Automatic Speech Recognition (ASR), a.k.a. speech-to-text (STT), transcribes it as a sequence of tokens, usually words

- Though increasingly as sub-words, like
 - Phones:
 - Character-by-character:
 - Spans of characters:



Consider what we want ASR to do



Aspects of ASR systems in the world

Speaking style: Read speech vs. spontaneous speech;

the latter contains many dysfluencies

(e.g., stuttering, uh, like, ...)

Accent, dialect: Mass-deployed or highly localized?

Vocabulary: Small (<20 words) or large (>50,000 words).

Words, phones, characters, sub-words?

Technical? Conversational?

• Channel: Cell phone? Noise-cancelling microphone?

Teleconference microphone?



Speech features

- Waveform inputs are very, very long
 - Usually: 1 second = 16,000 samples
- Dilated convolutional neural networks (CNNs) can learn & process the waveform directly
 - We will see an example of this in the TTS lecture
- Speech embeddings/representations can be learned with unsupervised objectives
 - The topic of CSC2518 this term
- The f-bank remains a convenient, fast, and widely used preprocessing step
- The result is always a sequence of speech feature vectors spaced 10s of milliseconds apart in time



A neural approach

We are given a sequence speech features

$$x = x_1, x_2, \dots, x_T, \qquad x_t \in \mathbb{R}^D$$

We want a sequence of tokens (a transcription)

$$y = y_1, y_2, ..., y_U, y_u \in \{1, 2, ..., V\}$$

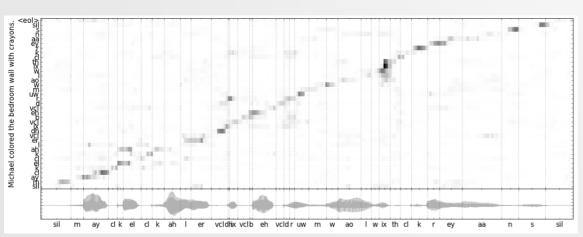
- y_u could be a character, word, phone, etc.
- $T \neq U$
- Sound familiar?
- We can do encoder/decoder NMT!
 - Source sequence (F) embeddings are now features (x)
 - Target sequences (E) are now transcriptions (y)



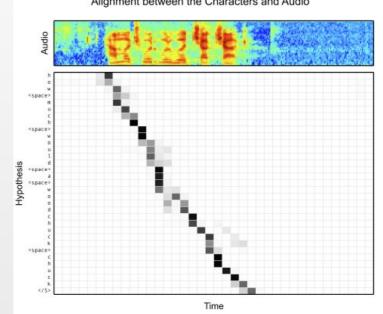
Encoder/decoder ASR

 Networks such as the Attention-based Encoder Decoder or Listen, Attend, and Spell are RNN-based encoder-decoders trained with teacher forcing (ML)

$$\mathcal{L} = -\sum_{u=1}^{U} \log P_{\theta}(y_u | y_{< u}, x)$$
Alignment



From Chorowski *et al.* (2014) "End-to-end continuous speech recognition using attention-based recurrent NN: First results"



From Chan et al. (2016) "Listen, attend, and spell"

Decoding

- Like in NMT, we approximate the hypothesis transcription $y^* = \operatorname{argmax}_y P_{\theta}(y|x)$
 - with the beam search algorithm
- For best performance, an external, auto-regressive language model may be incorporated into each time step via shallow fusion:

$$\log P_{\theta}'(y_{u}|y_{< u},x) \approx \log P_{\theta}(y_{u}|y_{< u},x) + \lambda \log P_{\xi}(y_{u}|y_{< u})$$
Total score

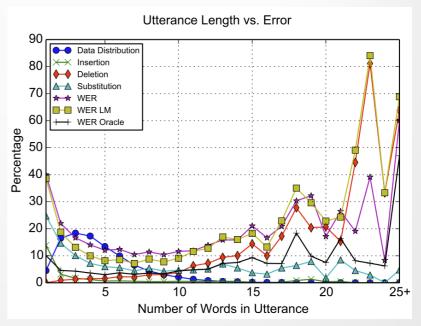
Encoder-decoder score

External LM score

• The impact of the external LM grows with λ

Pros and cons

- Encoder/decoder ASR with Transformers are often state-ofthe-art on ASR benchmarks
- They do have some drawbacks
 - They are unsuited to streaming (real-time transcription)
 - Performance suffers on long utterances

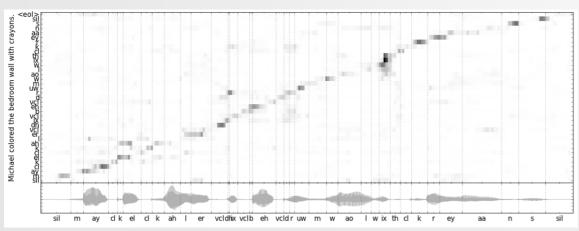


From Chan et al. (preprint) "Listen, attend, and spell"

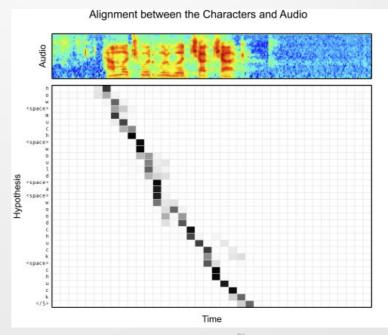


An alternative

- A decoder can attend to any hidden state h_1, \dots, h_T
- This is useful for NMT: tokens or phrases can be re-ordered, added, or removed
- But it is excessive in ASR: tokens are transcribed in the same order that they are uttered
- Can we exploit this monotonicity?

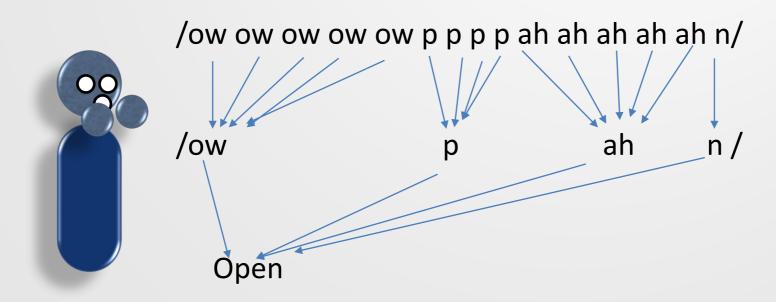


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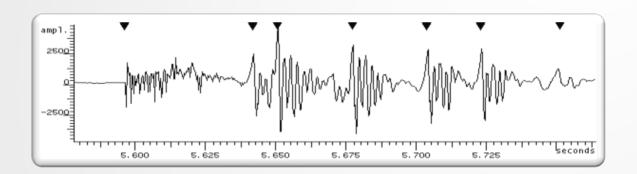
Recognizing speakers phones

- A first idea: since GMM can be used to recognize speakers, it can be used to recognize phones.
 - For each frame, a GMM (or DNN) classifies a phone.
 - Then we can look up to convert them into words! pronunciations





Some issues



- Speech changes over time
 - Per-frame decisions do not encode label order
 - This is valuable predictive context!
- During training, we don't know each frame's phone label!
 - We have "Open", not /ow ow ow ow ow p p p .../
 - How do we maximize the likelihood of "Open"?



Learning alignments

- We can solve both problems by learning monotonic alignments between sequences of frames and tokens
- To do so, both classic and end-to-end neural ASR rely on Dynamic Programming
 - Classic: Dynamic Time Warping (DTW), HMMs
 - E2E: Connectionist Temporal Classification (CTC), RNN-Transducer (RNN-T)
- DP can be used to align arbitrary sequences a and b
 - Error rates, bitext alignment, phrase-based SMT...
- The forward algorithm applies to all of these



A monotonic forward algorithm

```
Function monotonic_forward

Inputs a = a_1, a_2, ..., a_U and b = b_1, b_2, ..., b_T

1: Define table[0 ... U, 0 ... T]

2: initialize(table[0 ... U, 0], table[0, 1 ... T])

3: For each u in 1 ... U:

4: For each t in 1 ... T:

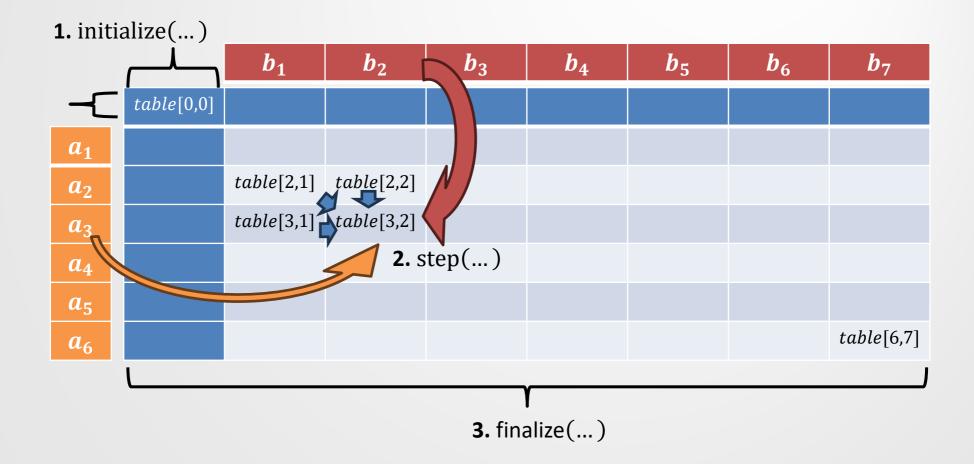
5: table[u, t] = table[u, t] = table[u, t]

6: Return finalize(table[0 ... U, 0 ... T])
```

- 1: Define $(U+1) \times (T+1)$ table *table* to store partial results
- 2: Initialize first row and column of table
- 3+4: Iterate over columns and rows with t and u
- 5: Use a_u , b_t , and left, up, and diagonal cells to compute table[u, t]
- 6: Use *table* to compute results

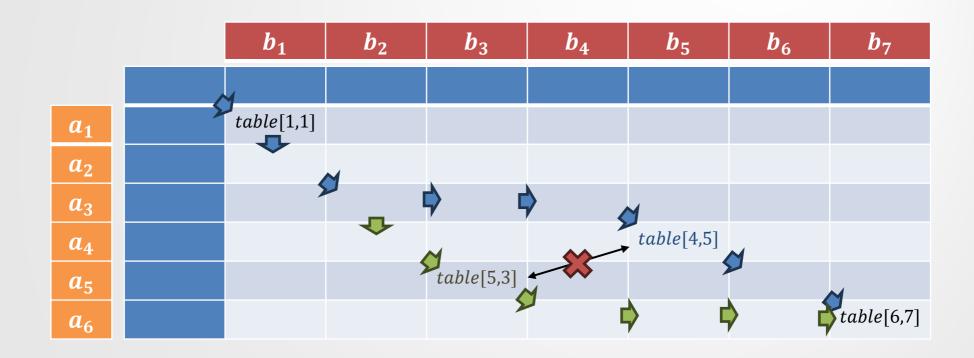


A graphical representation





Order of operations

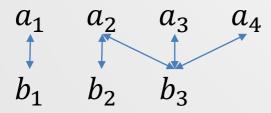


- Cells are populated in non-decreasing order of indices
 - table[u,t] depends on all table[u',t'] where $u' \le u$ and $t' \le t$
 - Not when either u' > u and/or t' > t

Which problems?

- We use monotonic_forward when solutions involve aligning each element of a to one from b and vice versa
- All elements of a and b must be aligned without crossing
- The solution may involve one or more alignments

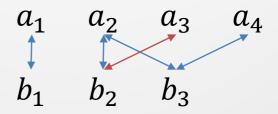
A valid alignment



$${a_1, b_1} \le {a_2, b_2} \le {a_2, b_3}...$$

 $... \le {a_3, b_3} \le {a_4, b_3}$

An invalid alignment



$$\{a_1, b_1\} \le \{a_2, b_2\} \le \{a_2, b_3\}...$$

...??? $\{a_3, b_2\} \le \{a_4, b_3\}$

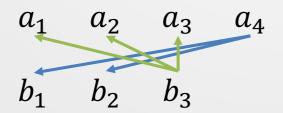
How?

- In DP, a problem is broken up into sub-problems which share computations
- For monotonic_forward, those sub-problems handle alignments of prefixes of a and b
- table[u, t] stores the solution for $\{a_1, ..., a_u\}, \{b_1, ..., b_t\}$
- All elements of the prefixes must also be aligned without crossing
- This guarantees that $\{a_u, b_t\}$ is part of **all** the alignments considered in table[u, t]
- Therefore, table[u,t] need only consider how to **correctly** extend a prefix with $\{a_u,b_t\}$



Aligning the last element

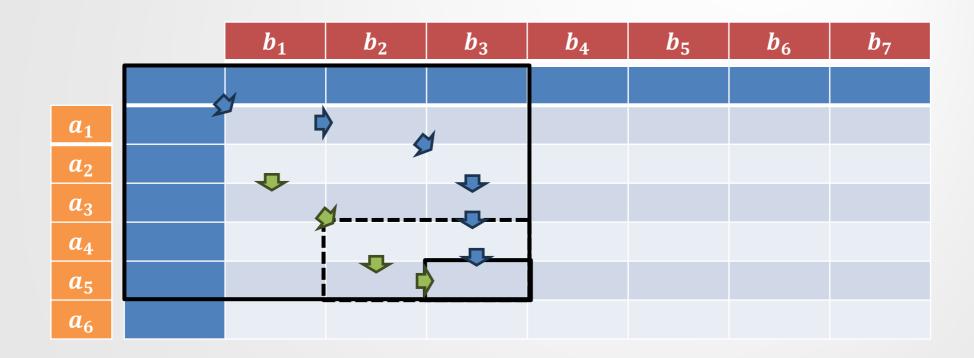
- We prove that $\{a_u, b_t\}$ must be part of table[u, t]
 - Suppose an alignment doesn't contain $\{a_u, b_t\}$
 - Recall: every element of $a_1, ..., a_u$ must align with some $b_1, ..., b_t$ without crossing (and vice versa)
 - Then $\{a_{u'}, b_t\}$ and $\{a_u, b_{t'}\}$ are in the alignment for some u' < u and t' < t
 - But these alignments cross!



(choose one blue line and one green; they always cross)



Which prefixes to extend?

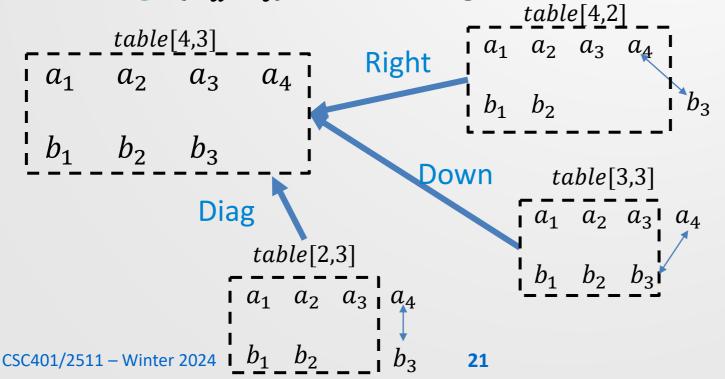


- Any cell table[u, t] must include one of $\{u 1, t 1\}, \{u 1, t\}$, or $\{u, t 1\}$
- table[u-1,t-1], table[u-1,t], and <math>table[u,t-1] include these
- We assume a correct solution can be derived by extending these cells



Extending prefixes

- table[u-1,t-1] table[u-1,t] table[u,t-1] table[u,t]
- The alignments in table[u, t] can extend an earlier prefix in one of three ways:
 - Right: b_t extends alignments in table[u, t-1]
 - Down: a_u extends alignments in table[u-1,t]
 - Diag: $\{a_u, b_t\}$ extends alignments in table[u-1, t-1]





General to specific

- To make our algorithm specific, we need answers to the following questions:
 - 1. What are a_u and b_t ?
 - 2. What is a solution to a prefix?
 - 3. How do we build the initial prefix(es) (base case)?
 - 4. How do we extend a prefix correctly (recursive step)?
 - 5. How is the result computed from *table*?
- Let's look at some examples

