CSCI 544, Lecture 15: Language models and speech recognition

Ron Artstein

2022-10-11

Administrative notes

No class on October 13

Coding Assignment 3 was due today

- ☛ Late sumbission by tomorrow with 10% penalty

Article selection for presentation due October 18

Coding Assignment 4 due October 25

Project:

Due Date	Task
November 3	Project status report
Nov 29/Dec 1	Poster presentations (in class)
December 1	Final report
December 3	Self-evaluation and peer grading

Article selection

- Each group selects an article for presentation.
- Select from top-tier NLP venues of 2022: ACL, NAACL, TACL, Findings of ACL, or Findings of NAACL.
- Put title and link on shared spreadsheet; check for conflicts.
  - Sheet accessible to USC Google accounts.
- Article does not need to be related to project.
- Pick article with interesting theme, point, or result.
  - If you cannot identify something interesting, choose a different article.
- Presentation does not have to cover the entire article.
- Presentation aimed for audience with the background covered in class.

Coding assignment 4

Write a Perceptron classifier

From scratch!

Corpus of hotel reviews

- Two classification problems: true/fake and positive/negative
- Two models: vanilla and averaged

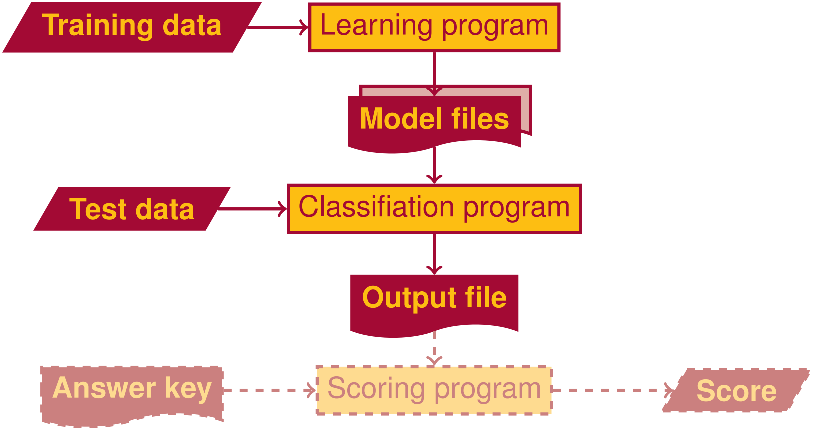
Graded on performance

Programming in Python

Submit on Vocareum

- Automatic feedback
- Submit early, submit often!

Coding assignment 4: programs



Coding assignment 4: notes

Problem formulation

Two binary classifiers: two sets of parameters

Features and tokenization

Experiment to see what works best!

. . . after you get the basic program working

Runtime efficiency

Compact representation

Don't multiply zeros

Over/underfitting

Choose number of iterations

Probability of a sentence

Does it make sense to talk about the probability of a sentence?

> or 'situations'. But it must be recognized that the notion 'probability of a sentence' is an entirely useless one, under any known interpretation of this term. On empirical grounds, the probability of my producing some given sentence of English – say, this sentence, or the sentence "birds fly" or "Tuesday follows Monday", or whatever – is indistinguishable from the probability of my producing a given sentence of Japanese.

Noam Chomsky. Quine's empirical assumptions.
Synthese 19(1/2): 53–68, 1968.

Language models

Probability of a sentence/utterance $\approx$
Probability of word given previous words

Unigram language model (bag of words): Independence assumption (similar to naïve Bayes)

$$P(w_1 \dots w_n) \approx \prod_i P(w_i) = P(w_1) \cdot P(w_2) \cdots P(w_n)$$

Bigram language model: Markov assumption

$$P(w_1 \dots w_n) \approx \prod_{i=0}^{n} P(w_{i+1}|w_i) = P(w_1|\#) \cdot P(w_2|w_1) \cdots P(\#|w_n)$$

N-gram language models

Trigram, 4-gram etc. use probabilities for longer word sequences

Some smoothing methods:

- Backoff: Use probability of highest available n-gram
- Interpolation: weighted mixture of trigram, bigram, unigram probabilities
- Etc.

Language models can give a **prior** probability on sentences

Human vocal tract (and some phonetics)

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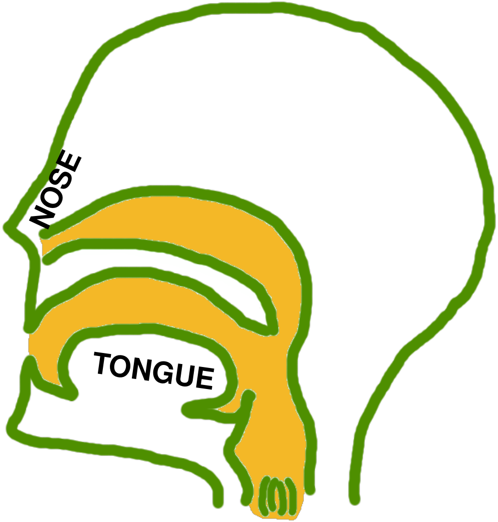

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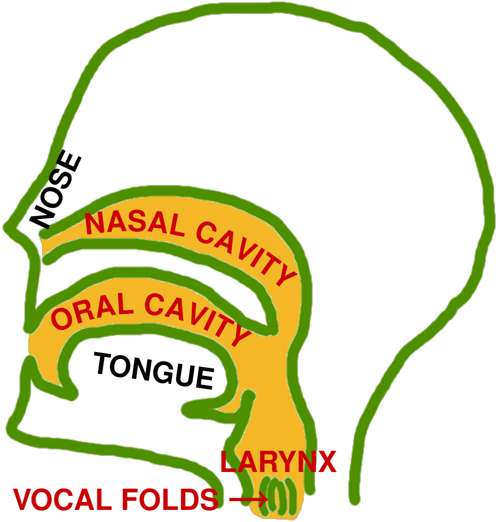

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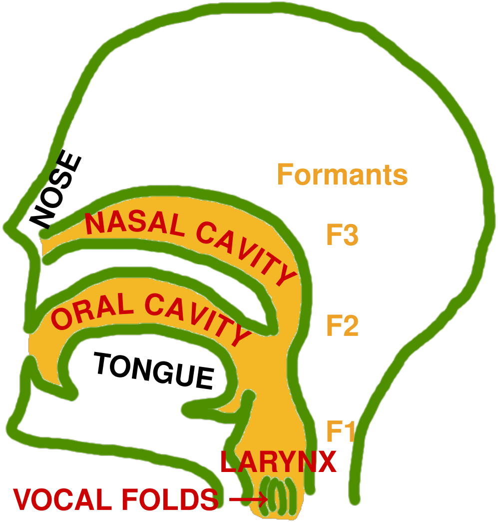

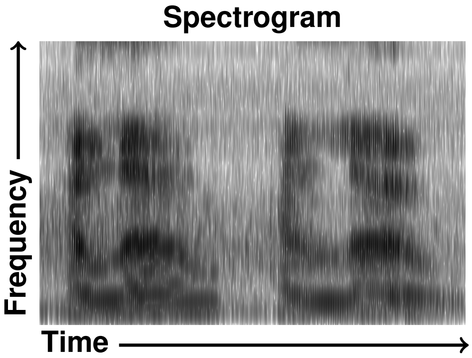

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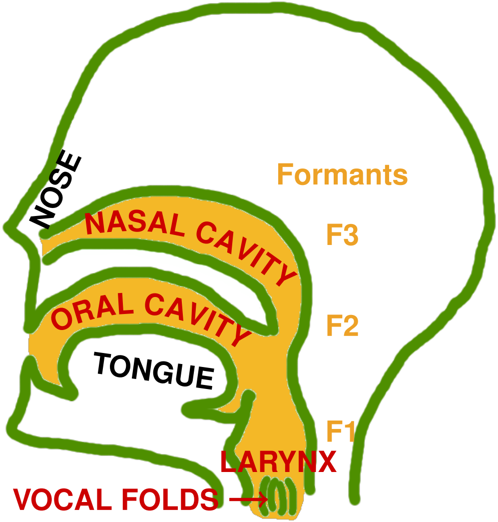

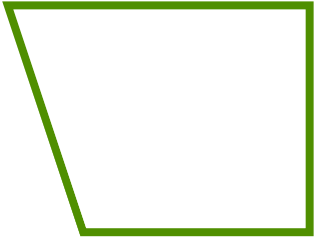

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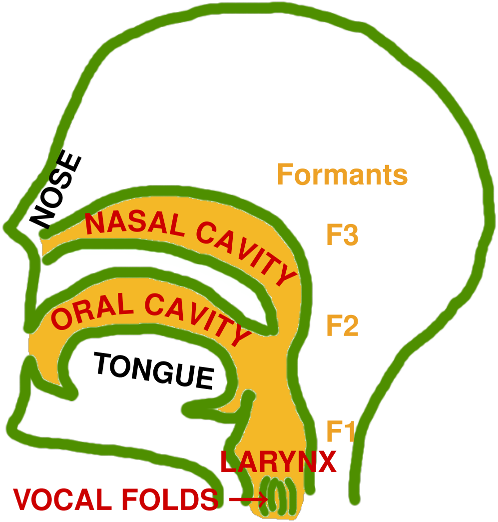

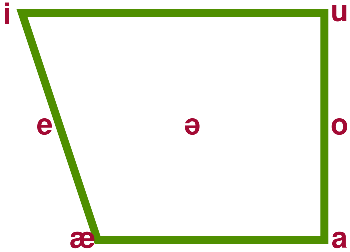

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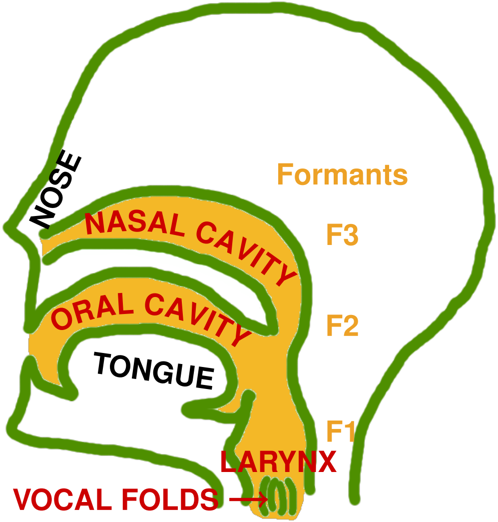

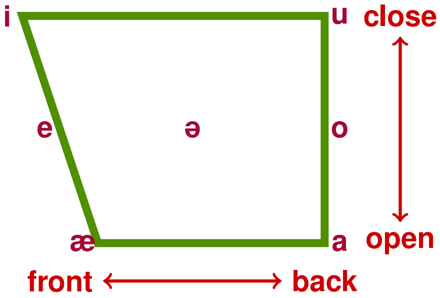

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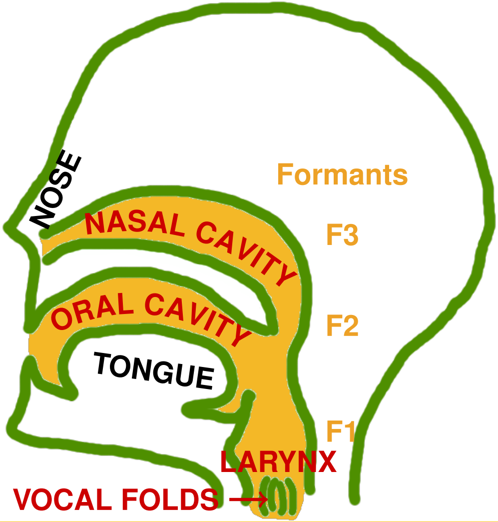
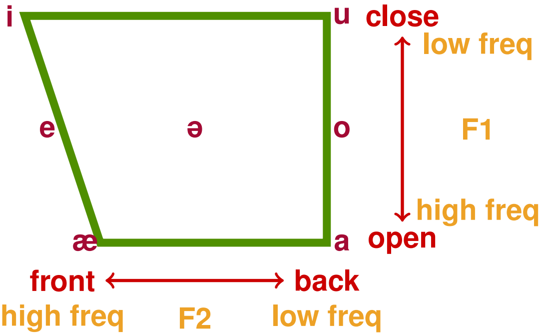




Speech recognition basics

Sample the waveform (e.g., every 10 msec)

Extract features

- Mel Frequency Cepstral Coefficients: MFCC
- Mel scale: pitch $\rightarrow$ perceptual pitch (works better)

Calculate $P(\text{word}|\text{sound})$

[word string] [time series of acoustic vectors]

Easier to calculate $P(\text{sound}|\text{word})$;
need prior distribution on word strings

$$P(\text{word}|\text{sound}) \propto \underbrace{P(\text{sound}|\text{word})}_{\text{[acoustic model]}} \cdot \underbrace{P(\text{word})}_{\text{[language model]}}$$

Words are too big…

Predict acoustic model from shorter units of sound: **phones**

	feeling					
IPA	f	i	l	ɪ	ŋ	(One character per phone)
ARPABET	F	IY	L	IH	NG	(Phones separated by spaces)

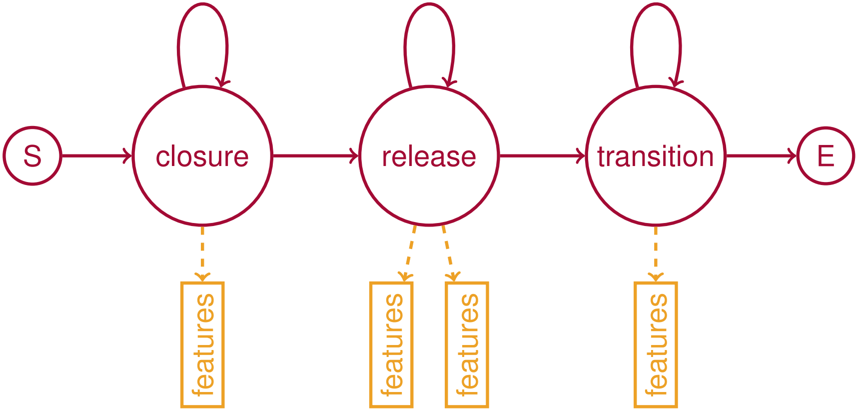
Vowels and voiced sounds have formants throughout

Stops are silent, affect formants before closure and after release

Phones modeled as 3-state HMMs: closure, release, transition

- States, transitions are discrete
- Observations are continuous:
  $P(\text{observation}|\text{state}) = \text{Normal}(\text{mean}, \text{variance})$

HMMs for phone recognition



Decoding speech

Find the most likely sequence of words, given a sequence of feature vectors

- Transitions *within* phones are for structure
- Transitions *between* phones constrained by language model and lexicon

Search through a lattice of hypotheses, with pruning (e.g. Viterbi decoding, beam search)

Speech recognition basics (review)

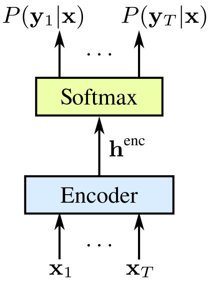
$$P(\text{word}|\text{sound}) \propto \underbrace{P(\text{sound}|\text{word})}_{\text{[acoustic model]}} \cdot \underbrace{P(\text{word})}_{\text{[language model]}}$$

- Acoustic model conditioned on phones
- Language model = distribution on words
- Phones and words linked by dictionary (lexicon)

Splitting the problem into acoustic and language models

- Acoustic model may vary by speaker
- Language model may vary by domain

Neural acoustic modeling: CTC



(a.) CTC

Graves et al., ICML 2006

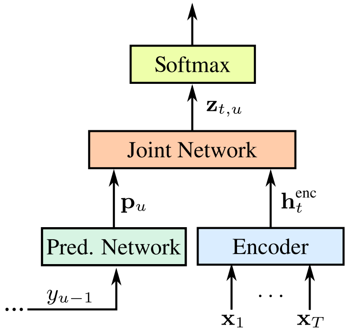
- Acoustic feature vectors $\rightarrow$ transcription symbols
- Output includes blank symbol
- ✔ Works well for phonetic transcription

From phonetic symbols to words: dictionary + LM

Prabhavalkar et al., Interspeech 2017

- ✘ Mapping acoustic feature vectors directly to characters doesn't work so well

Neural language modeling: RNN-Transducer



(b.) RNN-Transducer

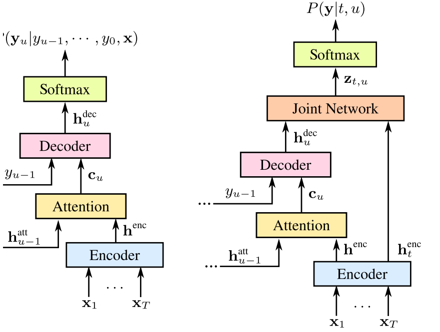
Graves, ICML workshop 2012

- Prediction network: dependencies between output symbols
- Analogous to a language model
- ✔ Predict phonetic transcription

Prabhavalkar et al., Interspeech 2017

- ✔ Mapping acoustic vectors to characters
- **Streaming** with unidirectional networks

Neural modeling: attention



c.) Attention-based Model (d.) RNN-Transducer with Attention

Chan et al., ICASSP 2016

- End-to-end: Listen-attend-spell

Attention: non-local dependencies

Prabhavalkar et al., Interspeech 2017

- ✔ Acoustic vectors to characters
- ✘ Difficulty with streaming

Chiu et al., ICASSP 2018

- Wordpieces instead of characters
- Other oprimizations

Evaluating speech recognizers

Word Error Rate: Levenshtein edit distance between reference and hypothesis

$$\text{WER} = \frac{\text{Deletions} + \text{Insertions} + \text{Substitutions}}{\text{Length of reference string}}$$

Ref: She is going to the beach
Hyp: She is **gone** to **am** the beach

$$\text{WER} = \frac{2}{6} = 33.3\%$$

Ref: I'm
Hyp: I am

$$\text{WER} = \frac{2}{1} = 200\%$$

Other measures: Concept Error Rate (what's a concept?)
Morpheme Error Rate
Phone Error Rate

Phones can match better than words

Speech:	Are you **married**	Word Error Rate
ASR:	Are you **Mary**	1/3 = 0.33

Speech:	AA R Y UW M EH R IY **D**	Phone Error Rate
ASR:	AA R Y UW M EH R IY	1/9 = 0.11

Speech:	Are **all** **soldiers** **deployed**	Word Error Rate
ASR:	Are **also** **just** **avoid**	3/4 = 0.75

AA R AO L S OW **L** JH **ER** **Z** **D** **IH** **P** **L** OY D	Phone Error Rate
AA R AO L S OW JH **IH** **S** **T** **AH** **V** OY D	7/16 = 0.44

Wang, Artstein, Leuski, Traum FLAIRS 2011