Automatic Speech Recognition: Introduction

Peter Bell

Automatic Speech Recognition— ASR Lecture 1
13 January 2020

Course details

- **Lectures:** About 18 lectures
- **Labs:** Weekly lab sessions – using Python, Kaldi (kaldi-asr.org and OpenFst (openfst.org))
  - Lab sessions in AT-3.09: Tuesdays 10:00, Wednesdays 10:00, Wednesdays 15:10, start week 2 (21/22 January)
  - Slots are allocated on Learn
- **Assessment:**
  - Exam in April or May (worth 70%)
  - Coursework (worth 30%, building on the lab sessions) (out on Thurday 13 February; in by Wednesday 18 March)
- **People:**
  - Lecturer: Peter Bell
  - TA: Andrea Carmantini

http://www.inf.ed.ac.uk/teaching/courses/asr/

Your background

If you have taken:

- Speech Processing *and* either of (MLPR or MLP)
  - Perfect!
- either of (MLPR or MLP) *but not* Speech Processing (probably you are from Informatics)
  - You'll require some speech background:
    - A couple of the lectures will cover material that was in Speech Processing
    - Some additional background study (including material from Speech Processing)
- Speech Processing *but neither of* (MLPR or MLP) (probably you are from SLP)
  - You'll require some machine learning background (especially neural networks)
    - A couple of introductory lectures on neural networks provided for SLP students
    - Some additional background study

Labs

- Series of weekly labs using Python, OpenFst and Kaldi
  - Labs are allocated on Learn
- Labs start week 2 (next week)
- Labs 1-4 will give you hands-on experience of building your own ASR system
  - **Note:** these labs are an important pre-requisite for the coursework
- Later labs will introduce you to Kaldi recipes for training acoustic models – useful if you will be doing an ASR-related research project

What is speech recognition?

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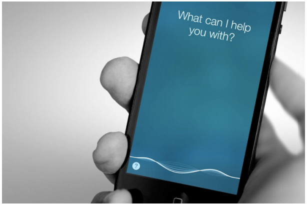

What is speech recognition?

Speech-to-text transcription

- Transform recorded audio into a sequence of words
- Just the words, no meaning.... But do need to deal with acoustic ambiguity: "Recognise speech?" or "Wreck a nice beach?"
- Speaker diarization: Who spoke when?
- Speech recognition: what did they say?
- Paralinguistic aspects: how did they say it? (timing, intonation, voice quality)
- Speech understanding: what does it mean?

Why is speech recognition difficult?

From a linguistic perspective

Many sources of variation

Speaker Tuned for a particular speaker, or speaker-independent? Adaptation to speaker characteristics

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- **Environment** Noise, competing speakers, channel conditions (microphone, phone line, room acoustics)
- **Style** Continuously spoken or isolated? Planned monologue or spontaneous conversation?

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Language spoken Estimated 7,000 languages, most with limited training resources; code-switching; language change

From a machine learning perspective

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- Hierachical and compositional nature of speech production and comprehension makes it difficult to handle with a single model

Example: recognising TV broadcasts

MGB CHALLENGE

The speech recognition problem

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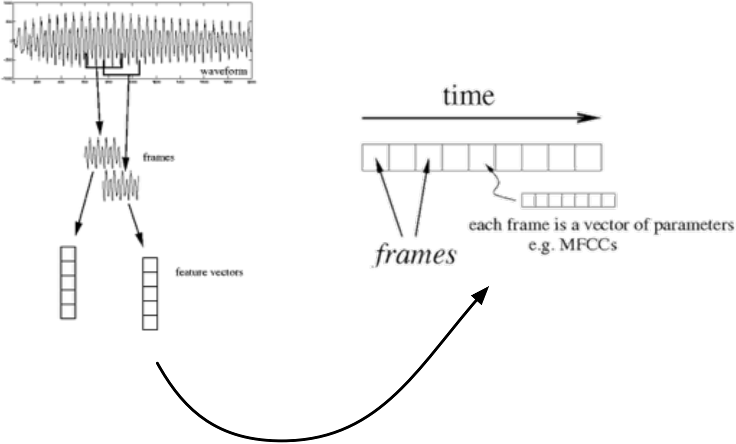
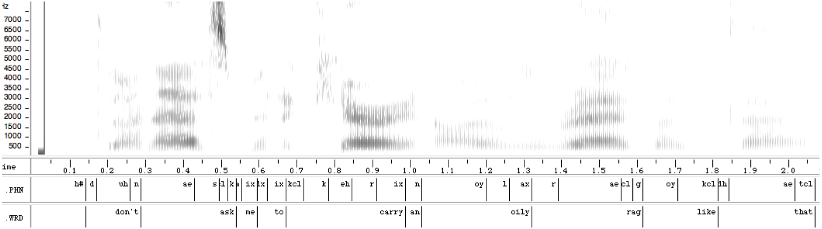
- At recognition time, our aim is to find the most likely $\mathbf{W}$, given $\mathbf{X}$
- To achieve this, statistical models are trained using a corpus of labelled training utterances $(\mathbf{X}^n, \mathbf{W}^n)$



Represent a recorded utterance as a sequence of *feature vectors*

Reading: Jurafsky & Martin section 9.3

Labelling speech (W)



Labels may be at different levels: words, phones, etc.
Labels may be *time-aligned* – i.e. the start and end times of an acoustic segment corresponding to a label are known

Reading: Jurafsky & Martin chapter 7 (especially sections 7.4, 7.5)

Two key challenges

In **training** the model:

Aligning the sequences $\mathbf{X}^n$ and $\mathbf{W}^n$ for each training utterance

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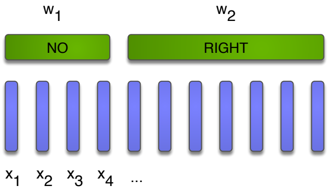

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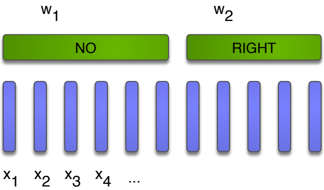

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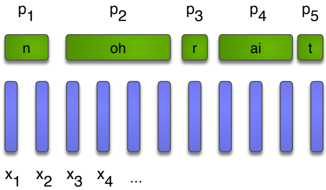

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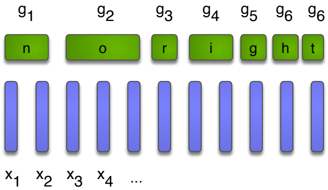

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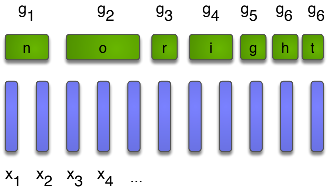

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Searching over all possible output sequences $\mathbf{W}$ to find the most likely one

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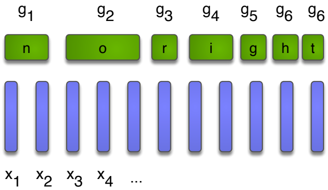

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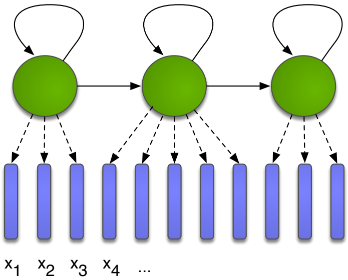
The **hidden Markov model** (HMM) provides a good solution to both problems

The Hidden Markov Model



- A simple but powerful model for mapping a sequence of continuous observations to a sequence of discrete outputs
- It is a **generative** model for the observation sequence
- Algorithms for training (forward-backward) and recognition-time decoding (Viterbi)

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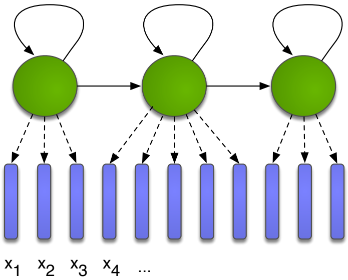

- A simple but powerful model for mapping a sequence of continuous observations to a sequence of discrete outputs
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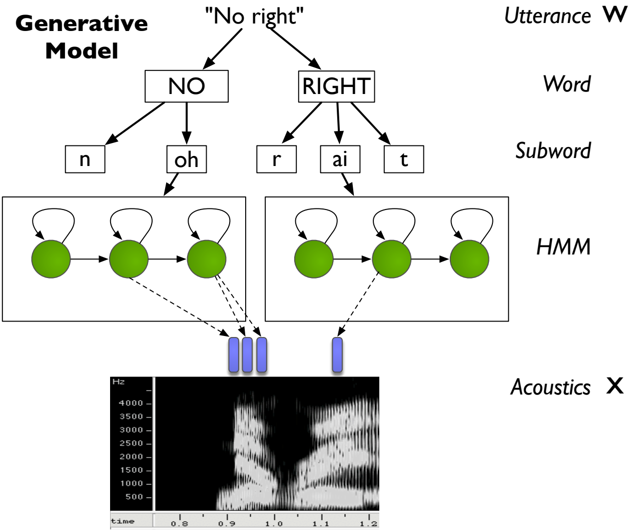
- Algorithms for training (forward-backward) and recognition-time decoding (Viterbi)
- Later in the course we will also look at newer all-neural, fully-differentiable "end-to-end" models

Hierarchical modelling of speech



"Fundamental Equation of Statistical Speech Recognition"

If $\mathbf{X}$ is the sequence of acoustic feature vectors (observations) and $\mathbf{W}$ denotes a word sequence, the most likely word sequence $\mathbf{W}^*$ is given by

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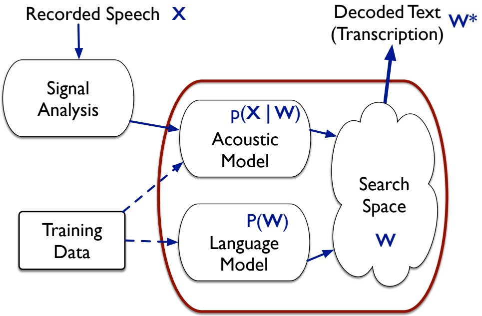
Applying Bayes' Theorem:

$$\begin{aligned} P(\mathbf{W} \mid \mathbf{X}) &= \frac{p(\mathbf{X} \mid \mathbf{W}) P(\mathbf{W})}{p(\mathbf{X})} \\ &\propto p(\mathbf{X} \mid \mathbf{W}) P(\mathbf{W}) \\ \mathbf{W}^* &= \arg\max_{\mathbf{W}} \underbrace{p(\mathbf{X} \mid \mathbf{W})}_{\text{Acoustic model}} \quad \underbrace{P(\mathbf{W})}_{\text{Language model}} \end{aligned}$$

Speech Recognition Components

$$\mathbf{W}^* = \arg\max_{\mathbf{W}} p(\mathbf{X} \mid \mathbf{W}) P(\mathbf{W})$$

Use an acoustic model, language model, and lexicon to obtain the most probable word sequence $\mathbf{W}^*$ given the observed acoustics $\mathbf{X}$



Phones and Phonemes

- **Phonemes**
  - abstract unit defined by linguists based on contrastive role in word meanings (eg "cat" vs "bat")
  - 40–50 phonemes in English
- **Phones**
  - speech sounds defined by the acoustics
  - many *allophones* of the same phoneme (eg /p/ in "pit" and "spit")
  - limitless in number
- Phones are usually used in speech recognition – but no conclusive evidence that they are the basic units in speech recognition
- Possible alternatives: syllables, automatically derived units, ...

(Slide taken from Martin Cooke from long ago)

Example: TIMIT Corpus

- TIMIT corpus (1986)—first widely used corpus, still in use
  - Utterances from 630 North American speakers
  - Phonetically transcribed, time-aligned
  - Standard training and test sets, agreed evaluation metric (phone error rate)
- TIMIT phone recognition - label the audio of a recorded utterance using a sequence of phone symbols
  - Frame classification – attach a phone label to each frame data
  - Phone classification – given a segmentation of the audio, attach a phone label to each (multi-frame) segment
  - Phone recognition – supply the sequence of labels corresponding to the recorded utterance

Basic speech recognition on TIMIT

- Train a classifier of some sort to associate each feature vector with its corresponding label. Classifier could be
  - Neural network
  - Gaussian mixture model
  - ...

  Then at run time, a label is assigned to each frame
- Questions
  - What's good about this approach?
  - What the limitations? How might we address them?

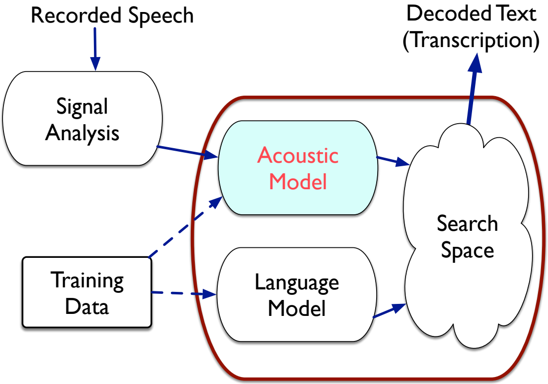
Evaluation

- How accurate is a speech recognizer?
- String edit distance
  - Use dynamic programming to align the ASR output with a reference transcription
  - Three type of error: insertion, deletion, substitutions
- Word error rate (WER) sums the three types of error. If there are N words in the reference transcript, and the ASR output has S substitutions, D deletions and I insertions, then:

$$\text{WER} = 100 \cdot \frac{S + D + I}{N} \% \qquad \text{Accuracy} = 100 - \text{WER}\%$$

- For TIMIT, define phone error error rate analagously to word error rate
- Speech recognition evaluations: common training and development data, release of new test sets on which different systems may be evaluated using word error rate

Next Lecture



Reading

- Jurafsky and Martin (2008). *Speech and Language Processing* (2nd ed.): Chapter 7 (esp 7.4, 7.5) and Section 9.3.
- General interest:
  - *The Economist Technology Quarterly*, "Language: Finding a Voice", Jan 2017.
    http://www.economist.com/technology-quarterly/2017-05-01/language
  - *The State of Automatic Speech Recognition: Q&A with Kaldi's Dan Povey*, Jul 2018.
    https://medium.com/descript/the-state-of-automatic-speech-recognition-q-a-with-kaldis-dan-povey-c860aada9b85