Automatic Speech Recognition: Introduction

Peter Bell

Automatic Speech Recognition— ASR Lecture 1
11 January 2020

Automatic Speech Recognition — ASR

Course details

- **Lectures:** About 18 lectures, delivered live on Teams for now
- **Labs:** Weekly lab sessions – using Python, OpenFst (openfst.org) and later Kaldi (kaldi-asr.org)
  - Lab sessions will start in Week 3 – exact format TBA.
- **Assessment:**
  - First five lab sessions worth **10%**
  - Coursework, building on the lab sessions, worth **40%**
  - Open book exam in April or May worth **50%**
- **People:**
  - Course organiser: Peter Bell
  - Guest lecturers: Hiroshi Shimodaira and Yumnah Mohammied
  - TA: Andrea Carmantini
  - Demonstrators: Chau Luu and Electra Wallington

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
- They count towards 10% of the course credit
- Labs start week 3 – exact arrangements TBA
- You will need to work **in pairs**
- Labs 1-5 will give you hands-on experience of using HMM algorithms to build your own ASR system
  - These labs are an important pre-requisite for the coursework – take advantage of the demonstrator support!
- Later optional 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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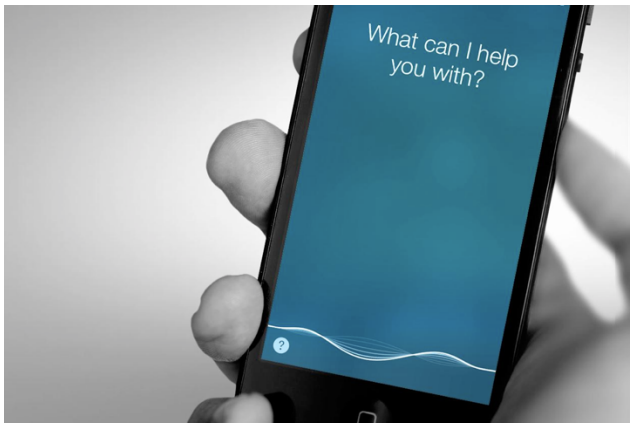

What is speech recognition?

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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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

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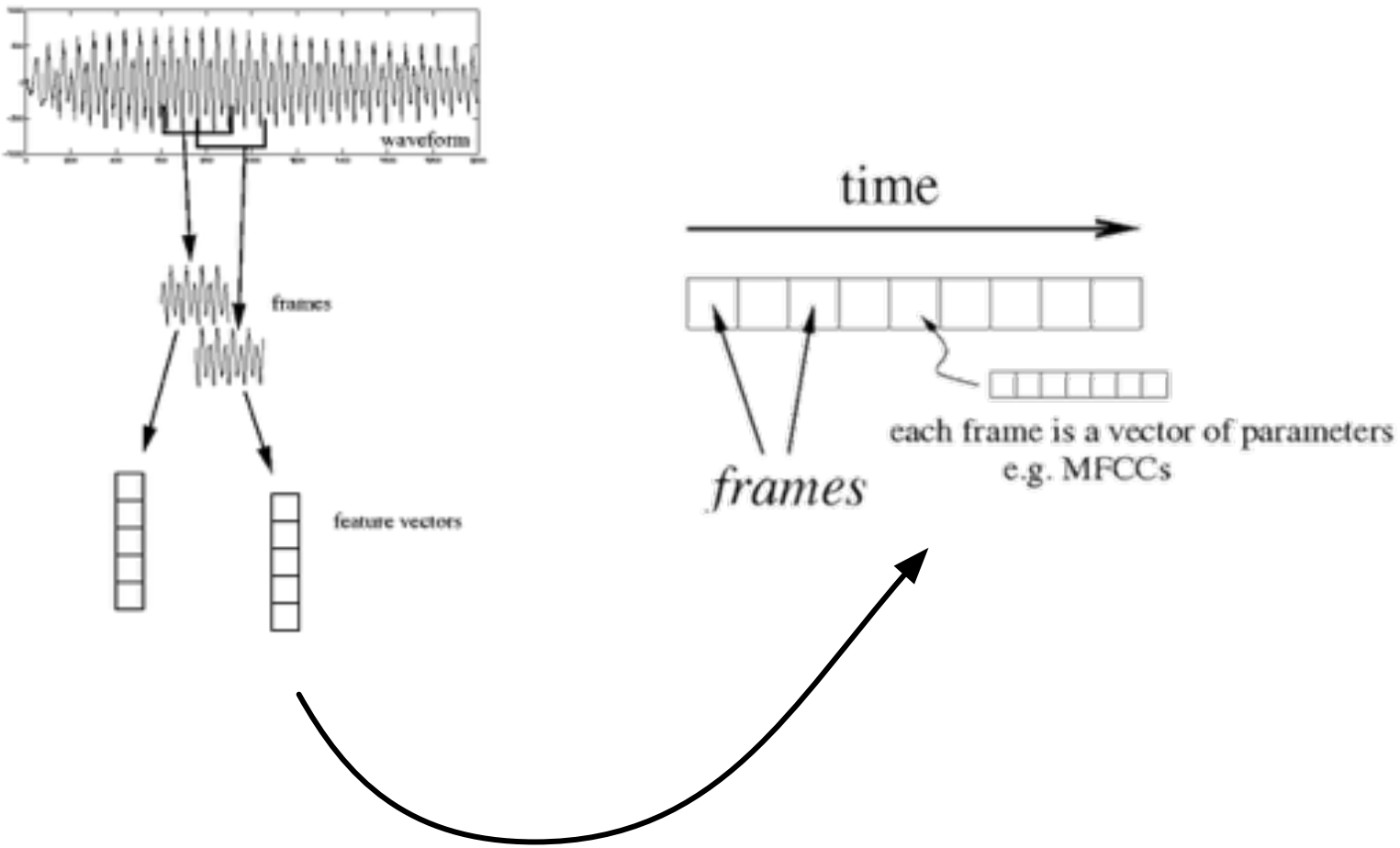
- At recognition time, our aim is to find the most likely W, given X
- To achieve this, statistical models are trained using a corpus of labelled training utterances (X^n, W^n)

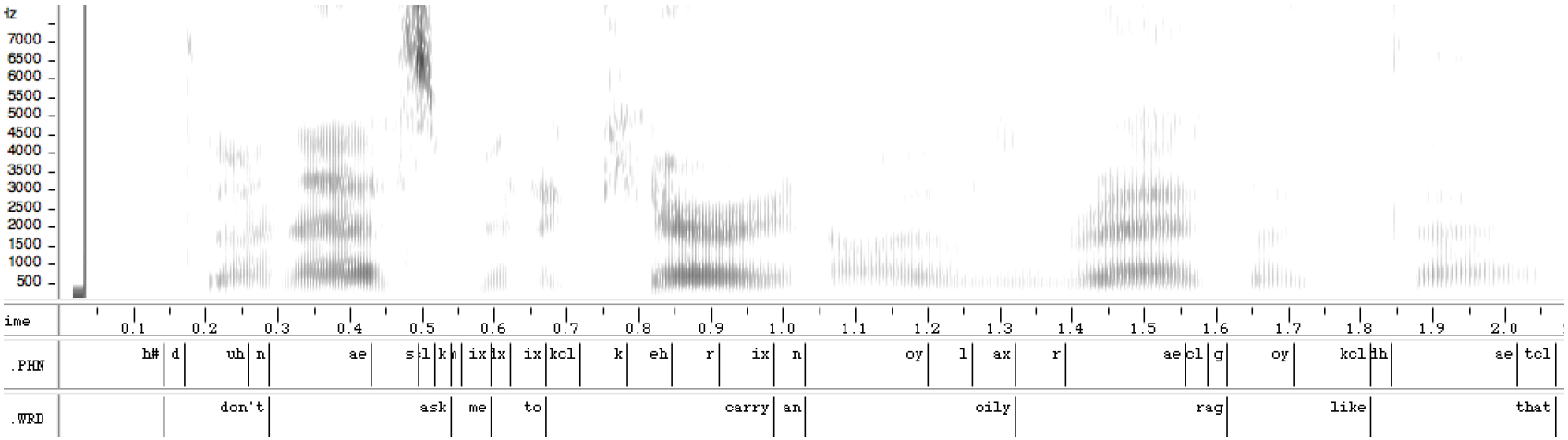
Representing recorded speech (X)



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 X^n and W^n for each training utterance

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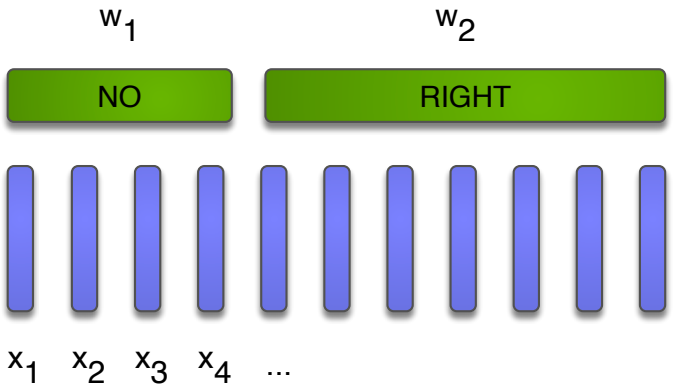

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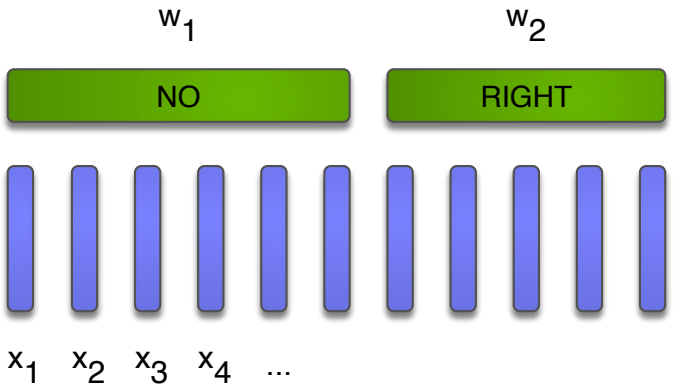

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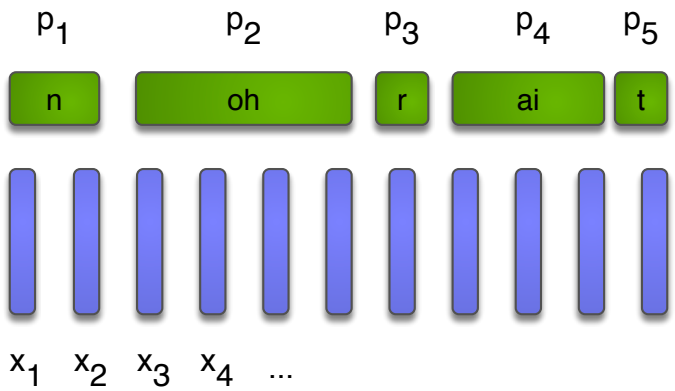

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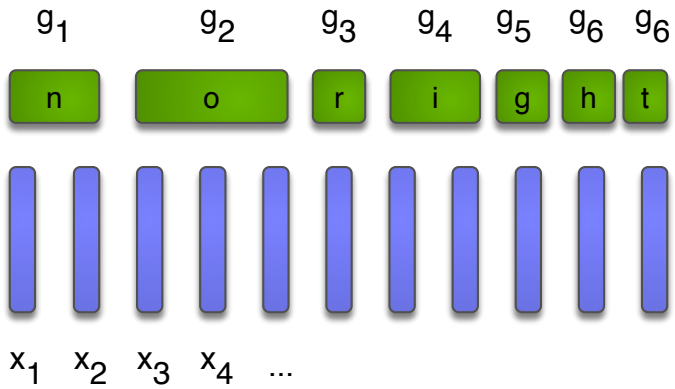

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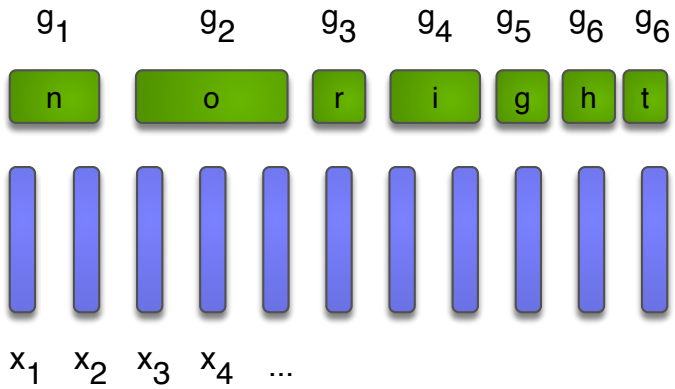

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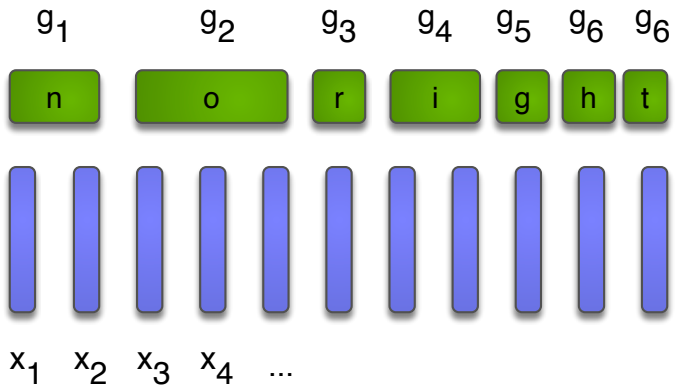

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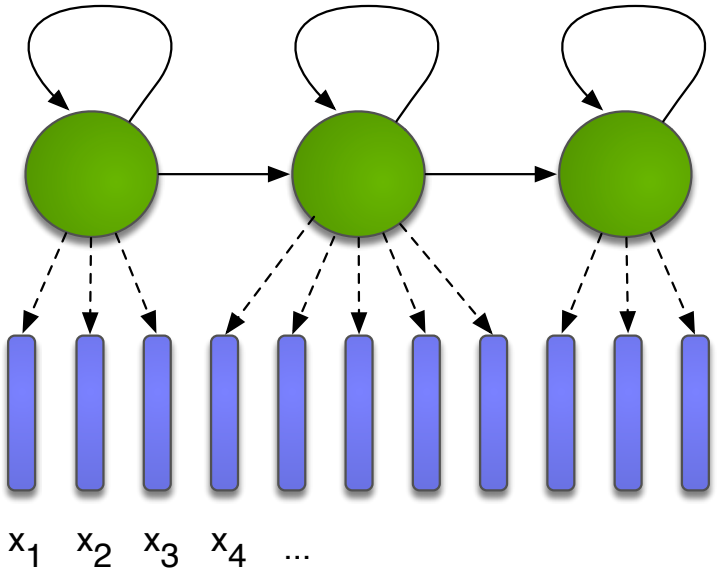
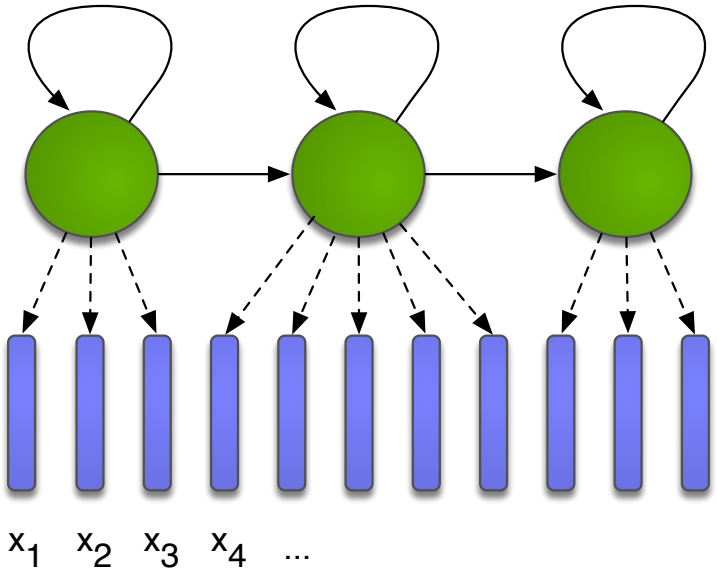
The **hidden Markov model** (HMM) provides a good solution to both problems

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)

The Hidden Markov Model



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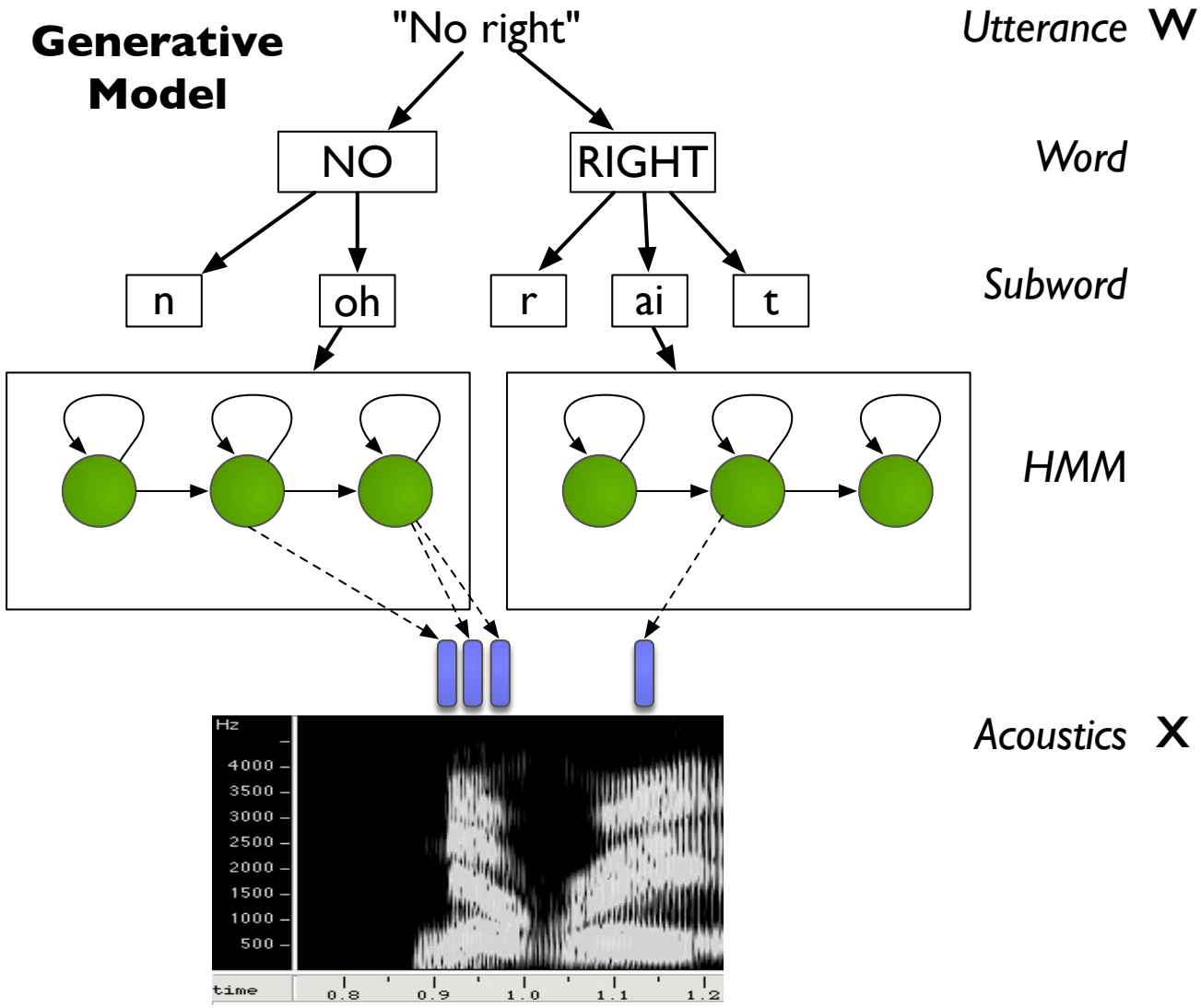
- It is a **generative** model for the observation sequence
- Algorithms for training (forward-backward) and recognition-time decoding (Viterbi)
- Later in the course we will also look at newer all-neural, fully-differentiable "end-to-end" models

Hierarchical modelling of speech



"Fundamental Equation of Statistical Speech Recognition"

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

$$W^* = \arg\max_W P(W \mid X)$$

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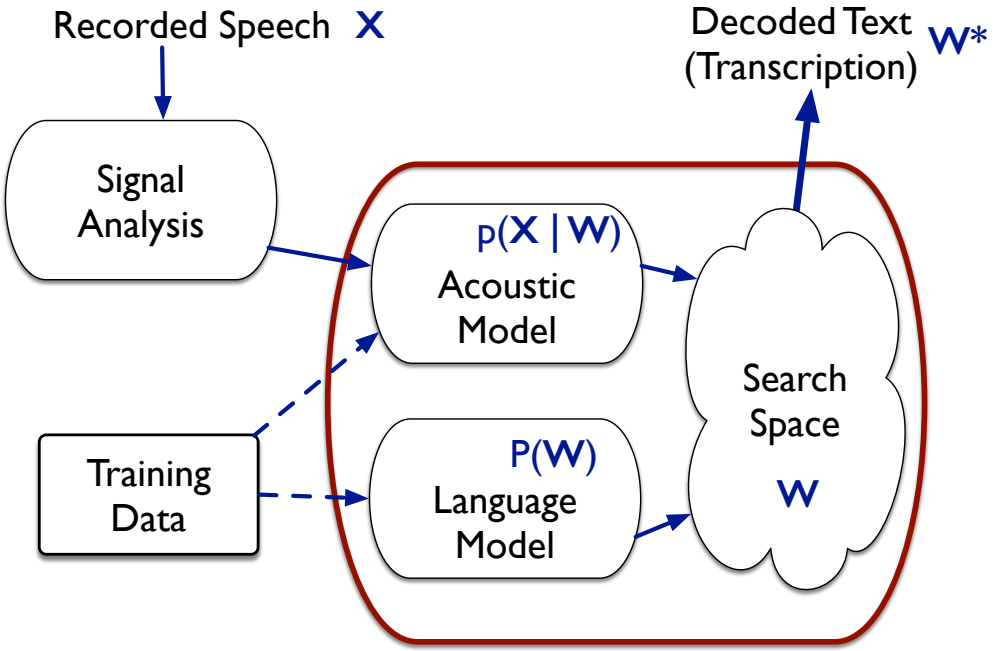
Applying Bayes' Theorem:

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

Speech Recognition Components

$$W^* = \arg\max_W p(X \mid W) P(W)$$

Use an acoustic model, language model, and lexicon to obtain the most probable word sequence W^* given the observed acoustics 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)

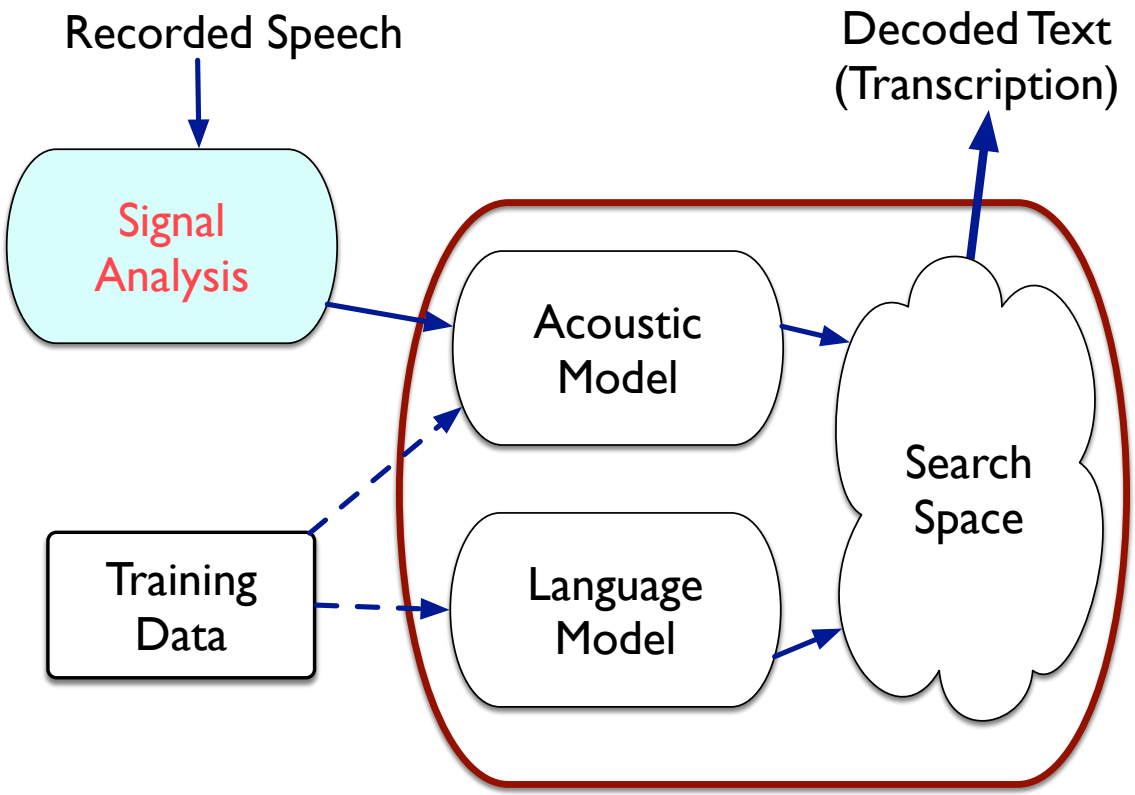
Evaluation

- 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:

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

- 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



Example: recognising TV broadcasts

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