Speech Recognition

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1 Introduction

By *automatic speech recognition* we mean the process of speech-to-text transcription: the transformation of an acoustic signal into a sequence of words, without necessarily understanding the meaning or intent of what was spoken. Recognition without understanding is not always possible since some semantic context may be required, for instance, to disambiguate "*Will the new display recognise speech?*" from "*Will the nudist play wreck a nice beach?*". Automatic speech recognition corresponds to answering the question *who spoke what when?*[1]; in the general case this may involve transcribing the speech of two or more people taking part in a conversation, in which the speakers frequently talk at the same time. The solution to this task is often considered in two parts: *speaker diarisation* (who spoke when?), and *speech to text transcription* (what did they say?). Of course, the speech signal contains much more information than just the words spoken and who said them. Speech acoustics also carries information about timing, intonation and voice quality. These paralinguistic aspects convey information about the speaker's emotion and physiology, as well as sometimes disambiguating between different possible meanings. In this chapter, however, we shall focus on automatic speech to text transcription.

Speech to text transcription has a number of applications including the dictation of office documents, spoken dialogue systems for call centres, hands-free interfaces to computers and the development of speech-to-speech translation systems. Each of these applications is typically more restricted than the general problem which requires the automatic transcription of naturally spoken continuous speech, by an unknown speaker in any environment. This is an

[1] This is sometimes referred to as speaker-attributed speech-to-text transcription.

extremely challenging task. There are several sources of variability which we cluster into four main areas: the *task domain*, *speaker characteristics*, *speaking style*, and the recognition *environment*. In many practical situations, the variability is restricted. For example, there may be a single, known speaker, or the speech to be recognised may be carefully dictated text rather than a spontaneous conversation, or the recording environment may be quiet and non-reverberant. In speech to text transcription a distinction is made between parts addressing acoustic variability (acoustic modelling), and parts addressing linguistic uncertainty (language modelling).

Task domain

Aspects of the specific speech recognition task which affect the difficulty of the speech transcription process include the language and the size of the vocabulary to be recognized, and whether the speech comes from a limited domain. Different languages present different challenges for a speech recognizer. For example, agglutinative languages, such as Turkish and Finnish, have larger vocabularies than non-agglutinative languages (such as English) due to words formed from the concatenation of multiple morphemes. This has an effect on lexical and language modelling. For English, a speech recognition system is considered to have a large vocabulary if it has the order of 10^4 word types in its vocabulary; a comparable system for a language such as Finnish however may have two orders of magnitude more word types. As another example, tonal languages, such as Chinese, use pitch movements to distinguish small sets of words which has an effect on acoustic modelling.

The number of word types in the vocabulary of a speech recognizer gives an indication of the "size" of the problem that however may be misleading;

perplexity[2] of the language model gives an indication of effective size. A spoken dialogue system concerned with stock prices, for instance, may have a relatively large vocabulary (due to the number of distinct words occurring in company names) but a small perplexity.

Speaker characteristics

Different speakers have differences in their speech production anatomy and physiology, speak at different rates, use different language, and produce speech acoustics with different degrees of intrinsic variability. Other differences in speaker characteristics arise from systematic variations such as those arising from speaker age and accent. One way to deal with this variability is through the construction of *speaker-dependent* speech recognition systems, but this demands a new system to be constructed for each speaker. *Speaker-independent* systems, on the other hand, are more flexible in that they are designed to recognize any speaker. In practice, a speaker-dependent speech recognition system will tend to make fewer errors than a speaker-independent system. Although speaker adaptation algorithms (section 2.5) have made great progress, it is still the case that the adaptability and robustness to different speakers exhibited by automatic speech recognition systems is very limited compared with human performance.

Style

In the early days of automatic speech recognition, systems solved the problem of where to locate word boundaries by requiring the speaker to leave pauses between words: the pioneering dictation product Dragon Dictate (Baker, 1989)

[2] An information theoretic measure of the expected number of words which may be expected to continue any word sequence, see chapter **??**.

is a good example of a large vocabulary *isolated word* system. However, this is an unnatural speaking style and most research in speech recognition is focused on *continuous* speech recognition, in which word boundary information is not easily available. The problem of continuous speech recognition thus involves segmentation into words, as well as labelling each word.

Until the mid-1990s most speech recognition research followed research in acoustic phonetics, using recordings of planned speech recorded in laboratory or quiet office conditions. However it has become apparent that more natural styles of speech, as observed in spontaneous conversation, result in considerably more acoustic variability: this is reflected in the increased word error rates for *conversational* or *spontaneous* speech recognition compared with the recognition of dictation or other *planned* speech. A modern speech recognition system for the transcription of dictated newspaper text results in a typical word error rate of 5–10%; a state-of-the-art conversational speech recognition system will result in a word error rate of 10–30% when transcribing spontaneous conversations (Chen *et al.*, 2006; Hain *et al.*, 2007a).

Environment

Finally, the acoustic environment in which the speech is recorded, along with any transmission channel can have a significant impact on the accuracy of a speech recogniser. Outside of quiet offices and laboratories, there are usually multiple acoustic sources including other talkers, environmental noise and electrical or mechanical devices. In many cases, it is a significant problem to separate the different acoustic signals found in an environment. In addition, the microphone on which the speech is recorded may be close to the talker (in the case of a headset or telephone), attached to a lapel, or situated on a wall or tabletop. Variations in transmission channel occur due to movements of the talker's head relative to the microphone and transmission across a telephone network or the internet. Probably the largest disparity between the accuracy of automatic speech recognition compared with human speech recognition occurs in situations with multiple interfering acoustic sources paired with a high degree of reverberation.

1.1 Learning from data

The standard framework for speech recognition is statistical, developed in the 1970s and 1980s by Baker (1975), a team at IBM (Jelinek, 1976; Bahl *et al.*, 1983) and a team at AT&T (Levinson *et al.*, 1983; Rabiner, 1989). In this formulation the most probable sequence of words $\mathbf{W}^*$ must be identified given the recorded acoustics $\mathbf{X}$ and the model $\boldsymbol{\theta}$:

$$\begin{aligned}
\mathbf{W}^* &= \arg\max_{\mathbf{W}} P(\mathbf{W} \mid \mathbf{X}, \boldsymbol{\theta}) && (1)\\
&= \arg\max_{\mathbf{W}} \frac{p(\mathbf{X} \mid \mathbf{W}, \boldsymbol{\theta}) P(\mathbf{W} \mid \boldsymbol{\theta})}{p(\mathbf{X} \mid \boldsymbol{\theta})} && (2)\\
&= \arg\max_{\mathbf{W}} p(\mathbf{X} \mid \mathbf{W}, \boldsymbol{\theta}) P(\mathbf{W} \mid \boldsymbol{\theta}) && (3)\\
&= \arg\max_{\mathbf{W}} \log p(\mathbf{X} \mid \mathbf{W}, \boldsymbol{\theta}) + \log P(\mathbf{W} \mid \boldsymbol{\theta}) && (4)
\end{aligned}$$

Equation (1) specifies the most probable word sequence as the one with the highest posterior probability given the acoustics and the model. Equation (2) follows from (1) through the application of Bayes' theorem; since $p(\mathbf{X} \mid \boldsymbol{\theta})$ is independent of the word sequence, we usually work with (3), or its log domain version (4). P denotes a probability and p denotes a probability density function (pdf). In what follows, the dependence on the model $\boldsymbol{\theta}$ (which is usually fixed) is suppressed to avoid notational clutter.

Equations (3) or (4) may be regarded as splitting the problem into two components: *language modelling* which is concerned with estimating the prior probability of a word sequence $P(\mathbf{W})$, and *acoustic modelling* where the likelihood of the acoustic data given the words, $p(\mathbf{X} \mid \mathbf{W})$, is estimated. The parameters of both of these models are normally learned from large annotated corpora of data. Obtaining the optimal word sequence $\mathbf{W}^*$ is the *search* or *decoding* problem, discussed further in section 3.

The language model $P(\mathbf{W})$, which is discussed further in chapter **??**, models a word sequence by providing a predictive probability distribution for the next word based on a history of previously observed words. Since this probability distribution does not depend on the acoustics, language models may be estimated from large textual corpora. Of course, the statistics of spoken word sequences are often rather different to the statistics of written text. The conventional n-gram language model, which approximates the history as the immediately preceding $n - 1$ words, has represented the state-of-the-art for large vocabulary speech recognition for twenty-five years. It has proven difficult to improve over this simple model (Jelinek, 1991; Rosenfeld, 2000). Attempts to do so have focused on improved models of word sequences (e.g. Bengio *et al.*, 2003; Blitzer *et al.*, 2005; Teh, 2006; Huang & Renals, 2007) or the incorporation of richer knowledge (e.g. Bilmes & Kirchhoff, 2003; Emami & Jelinek, 2005; Wallach, 2006).

In this chapter we focus on acoustic modelling, and the development of systems for the recognition of conversational speech. In particular we focus on the trainable hidden Markov model / Gaussian mixture model (HMM/GMM) for acoustic modelling, the choice of modelling unit, and issues including adaptation, robustness and discrimination. We also discuss the construction of a fielded system for the automatic transcription of multiparty meetings.

1.2 Corpora and evaluation

The statistical framework for ASR is extremely powerful: it is scalable and efficient algorithms to estimate the model parameters from a corpus of speech data (transcribed at the word level) are available.

The availability of standard corpora, together with agreed evaluation protocols, has been very important in the development of the field. The specification, collection and release of the TIMIT corpus (Fisher *et al.*, 1986) marked a significant point in the history of speech recognition research. This corpus, which has been widely used by speech recognition researchers for over two decades, contains utterances from 630 North American speakers, and is phonetically transcribed and time-aligned. The corpus defined training and test sets, together with a commonly agreed evaluation metric (phone error rate—analogous to word error rate discussed below). This resulted in a training and evaluation protocol enabling the exact comparison of results between researchers.

Since the release of TIMIT, many speech corpora with corresponding evaluation protocols have been released. These include corpora of domain-specific read speech (e.g. DARPA Resource Management), read aloud newspaper text (e.g. Wall Street Journal), domain-specific human-computer dialogues (e.g. ATIS), broadcast news recordings (e.g. Hub4), conversational telephone speech (e.g. Switchboard), and recordings of multiparty meetings (e.g. AMI). Many of these corpora are available from the Linguistic Data Consortium (`http://www.ldc.upenn.edu`); the AMI corpus is available from `http://corpus.amiproject.org`. The careful recording, transcription and release of speech corpora has been closely connected to a series of benchmark evaluations of automatic speech recognition systems, primarily led by the US National Institute of Standards and Technology (NIST). This cycle of data collection and system evaluation has given speech recognition research a solid objective grounding, and has resulted in consistent improvements in the accuracy of speech recognition systems (Deng & Huang, 2004)—although Bourlard *et al.* (1996), among others, have argued that an overly strong focus on evaluation can lead to a reduction in innovation.

If the speech recognition problem is posed as the transformation of an acoustic signal to a single stream of words, then there is widespread agreement on word error rate (WER) as the appropriate evaluation measure. The sequence of words output by the speech recognizer is aligned to the reference transcription using dynamic programming. The accuracy of the speech recognizer may then be estimated as the string edit distance between the output and reference strings. If there are N words in the reference transcript, and alignment with the speech recognition output results in S substitutions, D deletions, and I insertions, the word error rate is defined as:

$$\mathrm{WER} = 100 \cdot \frac{(S + D + I)}{N}\% \tag{5}$$

$$\mathrm{Accuracy} = (100 - \mathrm{WER})\%. \tag{6}$$

In the case of a high number of insertions, it is possible for the WER to be above 100%. Computation of WER is dependent on the automatic alignment between the reference and hypothesised sequence of words. As word timings are not used in the process this may lead to under-estimates of the true error rate in situations of considerable mismatch. In practice, the transition costs used in the dynamic programming algorithm to compute the alignment are standardized and embedded in standard software implementations such as the NIST sclite tool[3], or the HResults tool in the HTK speech recognition toolkit[4].

More generally, the desired output of a speech recognition system cannot always be expressed as a single sequence of words. Multiparty meetings, for instance, are characterised by multiple overlapping speakers. A measure of transcription quality for meetings might usefully include attributing each word to a meeting participant, as well as including timing information, to take account of overlaps.

[3] http://www.nist.gov/speech/tools
[4] http://htk.eng.cam.ac.uk/

2 Acoustic modelling

The statistical formulation of the speech recognition problem outlined in section 1.1 provides the basic framework for all state-of-the-art systems. The acoustic model, which is used to estimate $p(\mathbf{X} \mid \mathbf{W})$, may be interpreted as a generative model of a word sequence. Such a model must be decomposable into smaller units, since it is infeasible to estimate a separate model for each word sequence. Hidden Markov models (HMMs) (Baker, 1975; Poritz, 1988; Rabiner, 1989; Jelinek, 1998) have proven to be very well suited to this task.

HMMs are probabilistic finite state machines, which may be combined hierarchically to construct word sequence models out of smaller units. In large vocabulary speech recognition systems word sequence models are constructed from word models, which in turn are constructed from sub-word models (typically context-dependent phone models) using a pronunciation dictionary.

HMM acoustic models treat the speech signal as arising from a sequence of discrete phonemes, or "beads-on-a-string" (Ostendorf, 1999). Such a modelling approach does not (directly) take into account processes such as *coarticulation*, a phenomenon in which the place of articulation for one speech sound depends on a neighbouring speech sound. For instance, consider the phoneme `/n/` in the words "*ten*" and "*tenth*". In "*ten*", `/n/` is dental, with the tongue coming into contact (or close to) the upper front teeth; in "*tenth*", `/n/` is alveolar, with the tongue farther back in the mouth (coming into contact with the alveolar ridge). Coarticulation gives rise to significant context-dependent variability. The use of context-dependent phone modelling (section 2.3) aims to mitigate these effects, as does the development of richer acoustic models that take account of speech production knowledge (King *et al.*, 2007).

2.1 Acoustic features

Speech recognition systems do not model speech directly at the waveform level; instead signal processing techniques are used to extract the *acoustic features* that are to be modelled by an HMM.[5] A good acoustic feature representation for speech recognition will be compact, without losing much signal information. In practice the the acoustic feature representations used in speech recognition do not retain phase information, nor do they aim to retain information about the glottal source which (for many languages) is relatively independent of the linguistic message. Figure 1 shows a speech waveform and the corresponding *spectrogram*, a representation that shows the energy of the speech signal at different frequencies. Although a variety of representations are used in speech recognition, perhaps the most widely used are Mel frequency cepstral coefficients (MFCCs) (Davis & Mermelstein, 1980). MFCCs are based on the log spectral envelope of the speech signal, transformed to a nonlinear frequency scale that roughly corresponds to that observed in the human auditory system. This representation is smoothed and orthogonalised by applying a discrete cosine transform, resulting in a cepstral representation. These acoustic feature vectors are typically computed every 10ms, using a 25ms Hamming window within the speech signal. Perceptual linear prediction (PLP) is a frequently used alternative acoustic feature analysis, which includes an auditory-inspired cube-root compression and uses an all-pole model to smooth the spectrum before the cepstral coefficients are computed (Hermansky, 1990).

[5] The autoregressive hidden filter model (Poritz, 1982) is an intriguing alternative that performs modelling at the waveform level, and may be viewed as jointly optimising signal processing and acoustic modelling. However this approach relies on a linear prediction framework which is less powerful than the approaches employed in current systems.

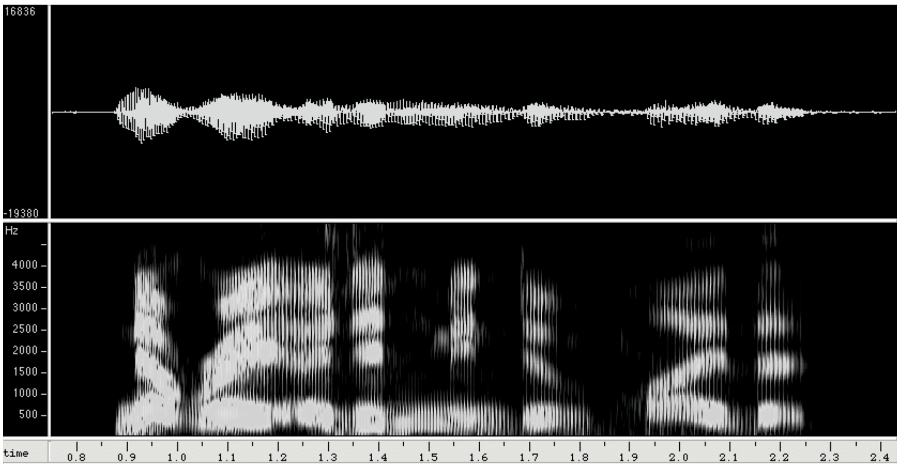


Figure 1. Waveform (top) and spectrogram (bottom) of conversational utterance "*no right I didn't mean to imply that*"

Speech recognition accuracy is substantially improved if the feature vectors are augmented with the first and second temporal derivatives of the acoustic features (sometimes referred to as the deltas and delta-deltas), thus adding some information about the local temporal dynamics of the speech signal to the feature representation (Furui, 1986). Adding such temporal information to the acoustic feature vector introduces a direct dependence between successive feature vectors, which is not usually taken account of in acoustic modelling; a mathematically correct treatment of these dependences has an impact on how the acoustic model is normalized—since fewer feature vector sequences will be consistent—and results in an approach we may be viewed as modelling an entire trajectory of feature vectors (Tokuda *et al.*, 2003; Bridle, 2004; Zhang & Renals, 2006; Zen *et al.*, 2007b).

Many state-of-the-art ASR systems use a 39-dimensional feature vector, corresponding to twelve MFCCs (or PLP cepstral coefficients), plus energy, along with their first and second derivatives. These acoustic feature representations have co-evolved with the basic acoustic models used in ASR: HMMs using multivariate Gaussian or Gaussian mixture output probability density functions, discussed in the next section. A particular advantage of cepstral representations compared with spectral representations is the decorrelation of cepstral coefficients, compared with the high correlations observed between neighbouring spectral coefficients. Such decorrelations are very well matched with the distributional assumptions that underlie systems based on Gaussians with diagonal covariance matrices.[6] Furthermore, the compact smoothed representations obtained when using MFCC or PLP coefficients results in component multivariate Gaussians of lower dimension than would be obtained if spectral representations were used.

Hermansky *et al.* (2000) introduced a class of acoustic features that attempt to represent discriminant phonetic information directly. These so-called *tandem* features, derived from phonetic classification systems, estimate phone class posterior probabilities and have proven to be successful when used in conjunction with conventional acoustic features. This is discussed further in section 5.2.

2.2 HMM/GMM framework

The statistical framework for ASR, introduced in section 1.1, decomposes a speech recogniser into acoustic modelling and language components (equations 3 and 4). Conceptually, the process works by estimating the probability of a hypothesised sequence of words $\mathbf{W}$ given an acoustic utterance $\mathbf{X}$ using a language model to estimate $P(\mathbf{W})$ (see chapter **??**) and an acoustic model to estimate $p(\mathbf{X}|\mathbf{W})$.

[6] Do not be misled however; a mixture of diagonal covariance Gaussians is able to model correlations between feature dimensions. But it is a relatively weak way of modelling such correlations.

We can regard the machine that estimates $p(\mathbf{X}|\mathbf{W})$ as a *generative model*, in which the observed acoustic sequence is regarded as being generated by a model of the word sequence. Acoustic models in speech recognition are typically based on hidden Markov models . An HMM is a probabilistic finite state automaton, consisting of a set of states connected by transitions, in which the state sequence is hidden. Instead of observing the state sequence, a sequence of acoustic feature vectors is observed, generated from a pdf attached to each state. A hierarchical approach is used to construct HMMs of word sequences from simpler basic HMMs. The building blocks of an HMM-based speech recognition system are HMMs of subword units, typically phones. A dictionary of pronunciations is used to build word models from subword models, and models of word sequences are constructed by concatenating word models. This approach, illustrated in figure 2, enables information to be shared across word models: the number of distinct HMM states in a system is determined by the size of the set of subword units. In the simplest case, an English speech recognition system might be constructed from a set of 40–60 base phone models with 3 states each. However, there is a lot of acoustic variability between different observed examples of the same phone. Much of this variability can be accounted for by the context in which a subword appears, and more detailed acoustic models can be achieved using context-dependent subwords, as discussed in section 2.3. Between-word silence can be represented by special HMMs for silence and, since between word silence is rare in continuous speech, adding a so-called “skip” transition to make their existence optional.

An HMM is parameterised by an initial or prior distribution over the states q_i, $P(q_i)$, a state transition distribution $P(q_j \mid q_i)$ and an output pdf for each state $p(\mathbf{x} \mid q_i)$, where $\mathbf{x}$ is an acoustic feature vector. This is illustrated in figure

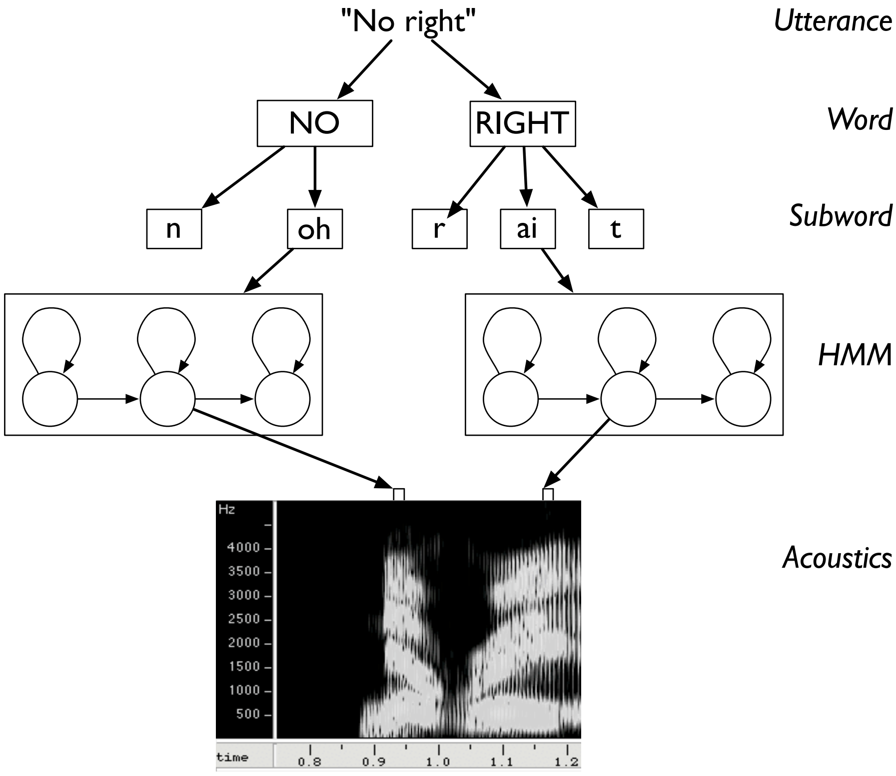


Figure 2. HMM-based hierarchical modelling of speech. An utterance model is constructed from a sequence of word models, which are each in turn constructed from subword models.

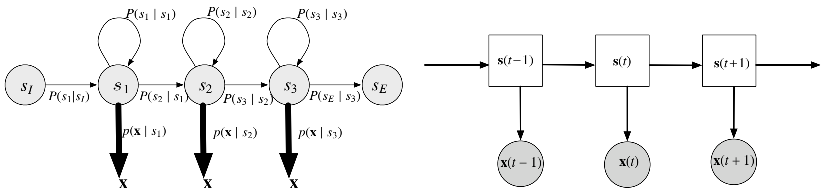


Figure 3. Representation of an HMM as a parameterised stochastic finite state automaton (left) and in terms of probabilistic dependencies between variables (right).

3 (left) in terms of the model parameters, and in terms of the dependences between the state and acoustic variables in figure 3 (right).

Each state has an output pdf defining the relation between the state and the acoustic vectors. A simple form for the output pdf for state q_i is a d-

dimensional Gaussian, parameterised by a mean vector $\boldsymbol{\mu}_i$ and a covariance matrix $\boldsymbol{\Sigma}_i$:

$$p(\mathbf{x}|q_i) = \mathcal{N}(\mathbf{x}; \boldsymbol{\mu}_i, \boldsymbol{\Sigma}_i) = \frac{1}{(2\pi)^{d/2}|\boldsymbol{\Sigma}_i|^{1/2}} \exp\left(-\frac{1}{2}(\mathbf{x}-\boldsymbol{\mu}_i)^T \boldsymbol{\Sigma}_i^{-1}(\mathbf{x}-\boldsymbol{\mu}_i)\right). \tag{7}$$

For a typical acoustic vector comprising 12th-order MFCCs plus energy, with first and second derivatives, $d = 39$.

Modelling speech using hidden Markov models makes two principal assumptions, illustrated in the graphical model shown in figure 3 (right):

(1) **Markov process**. The state sequence in an HMM is assumed to be a first-order Markov process, in which the probability of the next state transition depends only on the current state: a history of previous states is not necessary.

(2) **Observation independence**. All the information about the previously observed acoustic feature vectors is captured in the current state: the likelihood of generating an acoustic vector is conditionally independent of previous acoustic vectors given the current state.

These assumptions mean that the resultant acoustic models are computationally and mathematically tractable, with parameters that may be estimated from extremely large corpora. It has been frequently argued that these assumptions result in models that are unrealistic, and it is certainly true that a good deal of acoustic modelling research over the past two decades has aimed to address the limitations arising from these assumptions. However, the success of both HMM-based speech synthesis (Yamagishi *et al.*, 2009), as well as HMM-based speech recognition, is evidence that it is perhaps too facile to simply assert that HMMs are an unrealistic model of speech.

Acoustic modelling using HMMs has become the dominant approach due to the existence of recursive algorithms which enable some key computations to be carried out efficiently. These algorithms arrive from the Markov and observation independence assumptions. To determine the overall likelihood of an observation sequence $\mathbf{X} = (\mathbf{x}_1, \ldots, \mathbf{x}_t, \ldots, \mathbf{x}_T)$ being generated by an HMM, it is necessary to sum over all possible state sequences $q_1 q_2 \ldots q_T$ that could result in the observation sequence $\boldsymbol{X}$. Rather than enumerating every possible sequence, it is possible to compute the likelihood recursively, using the *Forward algorithm*. The key to this algorithm is the computation of the forward probability $\alpha_t(q_j) = p(\mathbf{x}_1, \ldots, \mathbf{x}_t, q_t = q_j \mid \boldsymbol{\theta})$, the probability of observing the observation sequence $\mathbf{x}_1 \ldots \mathbf{x}_t$ and being in state q_j at time t. The Markov assumption allows this to be computed recursively using a recursion of the form:

$$\alpha_t(q_j) = \sum_{i=1}^{N} \alpha_{t-1}(q_i) a_{ij} b_j(\mathbf{x}_t). \tag{8}$$

This recursion is illustrated in figure 4.

The decoding problem for HMMs involves finding the state sequence that is most likely to have generated an observation sequence. This may be solved using a dynamic programming algorithm, often referred to as *Viterbi decoding*, which has a very similar structure to the forward algorithm, with the exception that the summation at each time step is replaced by a max operation, since just the most probable state sequence is required. This is discussed further in section 3.

By *training* we mean the estimation of the parameters of an HMM: the transition probabilities and the parameters of the output pdf (mean vector and covariance matrix in the case of a Gaussian). The most straightforward

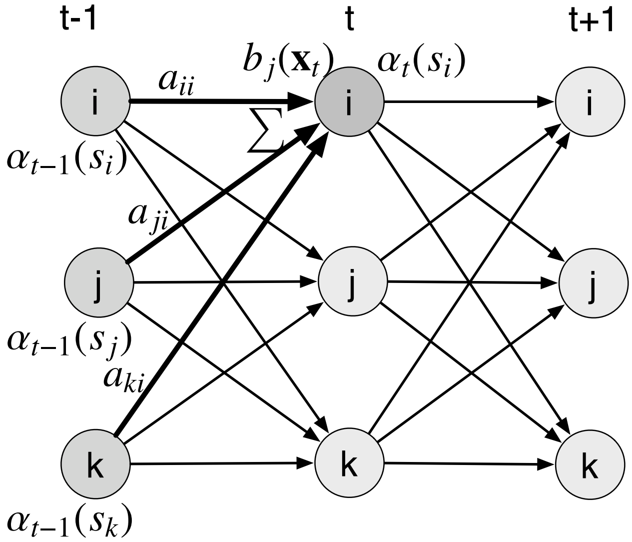


Figure 4. Forward recursion to estimate $\alpha_t(q_j) = p(\mathbf{x}_1, \ldots, \mathbf{x}_t, q_t = q_j \mid \boldsymbol{\theta})$

criterion to use for parameter estimation is maximum likelihood, in which the parameters are set so as to maximise the likelihood of the model generating the observed training data. Other training criteria may be used, such as maximum a posteriori (MAP) or Bayesian estimation of the posterior distribution, and discriminative training (section 2.4). Maximum likelihood training can be approximated by considering the most probable state-time alignment, which may be obtained using the Viterbi algorithm. Given such an alignment, maximum likelihood parameter estimation is straightforward: the transition probabilities are estimated from relative frequencies, and the mean and covariance parameters from the sample estimates. However, this approach to parameter estimation considers only the most probable path, whereas the probability mass is in fact factored across all possible paths. Exact maximum likelihood estimation can be achieved using the *forward-backward* or *Baum-Welch* algorithm (Baum, 1972), a specialisation of the expectation-maximization (EM) algorithm (Dempster *et al.*, 1977). Each step of this iterative algorithm consists of two parts. In the first part (the E step) a probabilistic state-time alignment is computed, assigning a *state occupation probability* to each state at each time, given the observed data. Then the M step estimates the parameters by an average weighted by the state occupation probabilities. The EM algorithm can be shown to converge in a local maximum of the likeihood function. The key to the E-step lies in the estimation of the state occupation probability, $\gamma_t(q_j) = P(q_t = q_j \mid \mathbf{X}, \boldsymbol{\theta})$, the probability of occupying state q_j at time t given the sequence of observations. The state occupation probabilities can also be computed reursively:

$$\gamma_t(q_j) = \frac{1}{\alpha_T(q_E)} \alpha_t(q_j) \beta_t(q_j), \tag{9}$$

where $\alpha_t(q_j)$ is the forward probability for state q_j at time t, $\beta_t(q_j) = p(\mathbf{x}_{t+1}, \mathbf{x}_{t+2}, \mathbf{x}_T \mid q_t = q_j, \boldsymbol{\theta})$ is called the *backward* probability and $\alpha_T(q_E)$ is a normalization factor (the forward probability for the end state q_E at the end of the observation sequence, time T). The backward probabilities are so called because they may be computed by a recursion that goes backwards in time.

The output pdfs are the most important part of this model, and restricting them to single Gaussians results in a significant limitation on modelling capability. In practice, Gassian mixture models (GMMs) are used as output pdfs. A GMM is a weighted sum of Gaussians:

$$p(\mathbf{x}|q_i) = \sum_{k=1}^{K} c_{ik} \mathcal{N}(\mathbf{x}; \boldsymbol{\mu}_{ik}, \boldsymbol{\Sigma}_{ik}), \tag{10}$$

where we have a mixture of K Gaussian components, with mixture weights c_{ik}. Training a GMM is analagous to HMM training: for HMMs the state is a hidden variable, for GMMs the mixture component is a hidden variable. Again the EM algorithm may be employed, with the E-step estimating the *component occupation probabilities*, and the M-step updating the means and covariances using a weighted average.

2.3 Sub-word modelling

As discussed in section 2.2, and illustrated in figure 2 there is no need to train individual HMMs for each sentence. Instead, the sentence HMMs can be constructed by concatenating word HMMs, which in turn may be constructed from subword HMMs. This is necessary as training of independent word models is not feasible for most applications: the Oxford English Dictionary contains more than 250 000 entries; for morphologically-rich languages, such as Finnish or Turkish, there are many more possible words.[7] If we assume that at least 50 samples per words are necessary and take the usually observed average word duration of half a second the required amount of speech transcribed speech data would be approximately 1700 hours. This calculation is however an underestimate as it does not take into account contextual effects, and assumes a uniform distribution over all words. It is only recently that such amounts of annotated data have been available, and only for US English. Thus subword modelling seems an attractive alternative: for example the words of British English can be described using a set of about 40–45 phonemes.

It is possible to write the pronunciation of words in a language with a finite set of symbols, hence one can associate an HMM with each. In the TIMIT database a set of 39 phones is often used; the ARPABET, a phoneme

[7] Note that derived forms are counted here as separate words whereas dictionaries such as the Oxford English Dictionary only list the base forms as independent entries

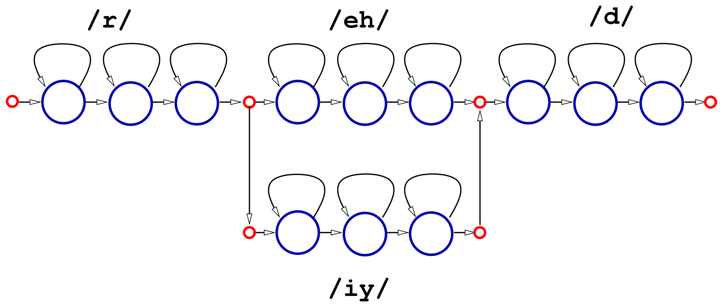


Figure 5. Hidden Markov models for phonemes can be concatenated to form models for words. Parallel paths indicate pronunciation variants.

set defined for speech recognition in US English, identifies 40 distinct symbols. By using HMMs for individual phonemes several important changes are made: a dictionary describing the transitions from words to phonemes has become necessary; the number of units has been drastically reduced; and the length of the units have become more similar. Albeit the TIMIT corpus was phonetically labelled this is not a necessary requirement for using models for phonemes as the phoneme sequence can be inferred from the word sequence using the dictionary and the sentence HMM is constructed by phoneme model concatenation. One issue arises in that the mapping from phonemes to words is not unique, for instance the word "*read*" can be pronounced in two ways, `/r iy d/` and `/r eh d`/. However, different pronunciations can be represented by using parallel paths in the sentence HMM (see figure 5). Even more so, different weights can be given to these variants. Pronunciation modelling and/or lexical modelling (e.g. Strik & Cucchiarini (1999)) usually focuses on how to best encode pronunciation variability.

Having less than 100 *small* HMMs does not allow to capture the large variability of speech, caused by individual variation in articulation and speaker differences (so called intra- and inter-speaker variability). In an attempt to deal with problems arising from acoustic phonetic context, such as coarticulation, many state-of-the-art systems are based on *context-dependent* phone models, often called *triphones*.

Triphone modelling has at its heart the idea of basic sounds that differ depending on their context. In particular the context here is given by the immediate neighbouring phonemes. Take for example the word "*sound*" and its ARPABET representation `/s ow n d/`. Instead of having a context-independent model for the phoneme `/ow/` a model for `/ow/` with left context `/s/` and right context `/n/` is constructed, typically written in the form `[s-ow+n]`. Taking a typical phoneme inventory size of 45 the number of such triphone models has now risen to 91 125 while retaining the trivial mapping from words to models. In order to avoid the same issues as with word models one however can start to declare some triphones as equivalent, e.g. `/ow/` may sound very similar with any fricative appearing beforehand.

Most state-of-the-art speech recognition systems make use of clustered triphones or even phone models in a wider context (e.g. quin-/penta-phones (Woodland *et al.*, 1995). A natural grouping approach would be knowledge based (e.g., Hayamizu *et al.*, 1988), but it has been repeatedly shown that automatic techniques give superior performance. As in many machine learning approaches clustering can operate bottom-up or top-down. The use of agglomerative clustering (Hwang & Huang, 1992) allows robust modelling but if not all triphones have been observed in the training data it is unclear how to represent words containing those triphones. Instead classification and regression trees (CART) were found to serve well in both cases (Bahl *et al.*, 1991; Young *et al.*, 1994). Here a binary decision tree is grown from a predefined set of questions about the neighbouring phonemes (e.g. if the left neighbour is a plosive). When growing the tree at each point the one question yielding the highest gain in likelihood is chosen. Tree growing is abandoned if the gain in likelihood falls below a predefined threshold. It is standard to cluster HMM states rather than whole models in this way and normally one decision tree per phoneme and per state position is derived. On average decision trees associated with vowels have greater depth than those associated with consonants.

Several weaknesses of the CART approach are known. For example, when clustering it is assumed that states are well represented by a single Gaussian density. Also, hard decisions are made on classes which are better represented as hidden variables (Hain, 2001), and the dependency on neighbouring phonemes is not the only property that influences sounds. Alternatives include articulatory representations or factorisation of graphical models (King *et al.*, 2007).

In English the relationship between sounds and the written forms is looser than in other languages, for example German or Turkish. For these languages it was shown that using the graphemes directly for modelling can have good results (Killer *et al.*, 2003) thus limiting the need for a manually crafted pronunciation lexicon. For tonal languages questions on tonal context, including the current phoneme, can significantly improve performance (Cao *et al.*, 2000).

2.4 Discriminative training

Learning of HMM parameters can be approached in fundamentally different ways. While generative learning tries to yield good estimates of the probability density of training samples, discriminative learning drives directly at finding those parameters that yield best classification performance. Within the generative family maximum likelihood (ML) training is the most widely used scheme. The associated objective function is given by

$$\mathcal{F}_{\text{ML}}\left(X\right) = \log p\left(\mathbf{X}, \boldsymbol{\theta}\right)$$

which implies that the parameters $\boldsymbol{\theta}$ are chosen to maximise the likelihood of the training data. As discussed in section 2.2 ML training can be efficiently carried out for HMMs, because the Baum-Welch algorithm enables the efficient computation of the state/component occupation probabilities, supplies good asymptotic guarantees, and is relatively easy to implement in software. Although the result of the algorithm is sensitive to the initialisation of parameters, practical experience has shown that this is usually of little impact on error rates obtained.

Discriminative training is based on the idea that, given finite training data and a mismatch of the model being trained to the true model, it is better to focus on learning the boundaries between the classes. Discriminative approaches have become increasingly popular and several techniques have been developed over the past two decades. The most important criteria are maximum mutual information (MMI), minimum classification error (MCE) and minimum Bayes Risk (MBR). All of these have in common that not only the correct, i.e. reference, sequence is used in training but also all incorrect word sequences. Since summation over all possible incorrect word sequences is not feasible for large vocabulary speech recognition the set of *competitors* is usually constrained to those that have significant probability mass compared with the correct sequence. This implies that the output of recognition of the complete training set must be generated, usually a computationally expensive process.

MCE training (Juang & Katagiri, 1992) is based on the idea that model parameters only need correction if misrecognition occurs. The objective function to be maximised is based on the ratio between the likelihoods of the correct sequence and of the incorrect ones. The discriminant function is defined as $d(\mathbf{X}|\boldsymbol{\theta}) = g(\mathbf{X}|\boldsymbol{\theta}) - \overline{g}(\mathbf{X}|\boldsymbol{\theta})$ where g denotes the log likelihood of the correct sentence and $\overline{g}$ is the average likelihood of the competitors $\mathcal{W}_{\text{incorrect}}$:

$$\overline{g}(\mathbf{X}|\boldsymbol{\theta}) = \frac{1}{\eta} \log \left(\frac{1}{M-1} \sum_{\mathbf{W} \in \mathcal{W}_{\text{incorrect}}} \exp\left(\eta \log p(\mathbf{X}|\mathbf{W}, \boldsymbol{\theta})\right) \right)$$

Instead of using the above function directly the transition is smoothed with a sigmoid function, which serves as an approximation to a zero/one loss function (i.e. if the value of the discriminant function is larger or smaller than zero). The overall criterion function again is an average over all training samples of the smoothed discriminants. MCE training is mostly used for smaller vocabularies. Its main weakness is the inefficient use of training data since it only considers misrecognised examples. By allowing the smoothed functions to become a step function and the weight η to tend towards ∞ the criterion function can be shown to converge to the misclassification rate and hence has a clear relationship to MBR training (outlined below).

A recently more prominent alternative is MMI training. Albeit being introduced at a similar time (discrete densities, Nadas *et al.* (1988), continuous Normandin (1991)) it was initially feasible only for small vocabulary tasks or even discrete word recognition, partially because of the substantial computational cost incurred. The improvements in accuracy for smaller tasks were substantial. The first large vocabulary implementation was reported by Valtchev *et al.* (1997) but the gains were modest in comparison. The MMI objective function is given by

$$\mathcal{F}_{\mathrm{MMI}}\left(\boldsymbol{\theta}\right)=\mathcal{E}\left\{\frac{p(\mathbf{X}|\mathbf{W},\boldsymbol{\theta})}{p(\mathbf{X}|\boldsymbol{\theta})}\right\}=\mathcal{E}\left\{\frac{p(\mathbf{X}|\mathbf{W},\boldsymbol{\theta})}{\sum_{\mathbf{W}'\in\mathcal{W}_{\mathrm{incorrect}}}p(\mathbf{X}|\mathbf{W}',\boldsymbol{\theta})^{\alpha}P(\mathbf{W}'|\boldsymbol{\theta})^{\beta}}\right\} \tag{11}$$

where $\mathcal{E}\left\{\cdot\right\}$ denotes the expectation. This is equivalent to the mutual information between word sequence $\mathbf{W}$ and acoustic features $\mathbf{X}$. Naturally the amount of information transferred is to be maximised. The criterion has an equivalent interpretation as a variant of conditional maximum likelihood (Nadas, 1983). Optimisation of the above criterion is mostly based on the extended Baum-Welch algorithm (Gopalakrishnan *et al.*, 1989). In contrast to the standard Baum-Welch algorithm a learning rate factor similar to gradient descent algorithms was introduced. The selection of the optimal learning rate is difficult and was found to best be set such that the variances of the updated model parameters remain sufficiently positive. Nevertheless usually after only a few iterations the algorithms tend to diverge.

Povey (2003) introduced two fundamental improvements that allowed not only to stabilise the algorithm, but also improved performance on large vocabulary tasks dramatically. Equation 11 shows two so far unexplained factors α and β. These factors allow to scale the contribution of the acoustic and language model components. Such scaling would be of no effect in ML training but equation 11 involves a sum. Scaling the language model scores is important in decoding (see section 3) with the rationale that acoustic models under-estimate the true likelihoods due to independence assumptions. The rationale in MMI training is identical, with even the same scale factor values being used (or the inverse to scale the acoustics down rather the language model up). Secondly smoothing of the update equation proved to be important. The ML estimate serves as a much more stable estimate and the addition of fixed amounts of the MMI parameter updates was shown to greatly enhance the stability of the algorithm and thus improve performance. In Povey (2003) so-called I-smoothing adds a predefined weight to the ML estimate in the update equations.

Both MCE and MMI training have interesting interpretations that are intuitive and fit in well with ML training. However, in both cases one assumption is made that is in conflict with the decoding scheme, namely the use of likelihood to assess the correctness of a sentence. This correctness measure then drives the update of parameters. Speech recogniser output however is normally assessed with the word error metric which measures performance in the form of insertions, deletions and substitutions of words (aka minimum edit or Levenshtein distance). For MCE and MMI the word error rate is of no concern, as long as the likelihood of an incorrect sentence is close to the correct little change is made on the associated HMM parameters.

To alleviate this shortcoming minimum Bayes risk training was introduced, initially in the form of so-called Minimum Phone Error (MPE) training (Povey & Woodland, 2002). Here explicit use is made of the Levenshtein string-edit distance between the competing and reference utterances, $L(\mathbf{W}, \mathbf{W}_{\text{ref}})$. The objective function is given by

$$\mathcal{F}_{\text{MBR}}(\boldsymbol{\theta}) = \sum_{\mathbf{W} \in \mathcal{W}} L(\mathbf{W}, \mathbf{W}_{\text{ref}}) P(\mathbf{W}|\mathbf{X}, \boldsymbol{\theta})$$

The posterior probability of the competing utterances is weighted by the amount of error in the target metric. Optimisation of this criterion is more complicated because, as before the above sum cannot be computed exactly. Whereas in the case of MMI the HMM properties allow reformation at state level this becomes more complicated here. The error rate is associated with a whole sentence and the error value of a single word is not well defined as the edit distance has no relation to time, i.e. the only errors of the token string are measured. In order to alleviate this problem two steps can be taken. On the one hand a move to smaller units and the measurement of local error led to the MPE criterion function.

$$\mathcal{F}_{\text{MPE}}\left(\boldsymbol{\theta}\right) = \frac{\sum_{\mathbf{R}} P(\mathbf{X}|\mathbf{R},\boldsymbol{\theta})P(\mathbf{R})A(\mathbf{R},\mathbf{R}_{\text{ref}})}{\sum_{\mathbf{R}} P(\mathbf{X}|\mathbf{R},\boldsymbol{\theta})P(\mathbf{R})}$$

where $\mathbf{R}$ is a sequence of phonemes and $\mathbf{R}_{\text{ref}}$ is the sequence associated with the reference words, and $A\left(\cdot\right)$ denotes the count of raw phoneme errors. It can be shown that maximisation of this function leads again to the extended Baum-Welch equations and updates similar to those obtained for MMI if the phoneme distance is replaced by a local estimate (Povey, 2003) based on an approximation of frame overlap. Gibson (2008) provided a formal proof of local convergence.

Discriminative training allows significant gains in word error rate. On most large vocabulary tasks 10-20% relative improvement in word error rate are typically found in comparison to ML trained models which in most cases also serve as the starting point for training. The rate of improvement is rather dependent on model set size and both MMI and MPE training allow much more compact models. Original work on large–scale MMI training postulated that gains increased with an increase in the amount of data (Woodland & Povey, 2000), which is very different to the behaviour observed for ML training. The computational cost of discriminative training is high and the complex solutions for optimisation cause sub-optimality in other areas such as speaker adaptation (see Section2.5). Naturally discriminative training is sensitive to the quality of the reference labels.

2.5 Speaker adaptation

Speech signals vary substantially without significant changes in human perception. A single person can vary the signal due to context, mood, or prosody. Despite the range of intra-speaker variations listeners are easily capable of discerning different speakers. The differences are manifold and are a mixture of general speech behaviour but also the physical characteristics of a person. The vocal tract shape, lungs and vocal cords give a distinct characteristic to a person's voice. These characteristics are not as unique as fingerprints but are sufficient to yield significant distinction in forensic applications. For the reminder of this section we focus on acoustic adaptation rather than adaptation to linguistic differences as it is to date the far more common form of adaptation. Nevertheless lexical and even language models can be adapted to learn speaker specific characteristics (Bellegarda, 2004; Strik & Cucchiarini, 1999).

The natural variability of speech sounds themselves (aside from distortions introduced by the environment) is the main source of confusion and cause of errors. For the reasons outlined above it seems logical to separate physical variations from intentional ones. Hence the initial focus of speech recognition research was in the development of systems capable of dealing with a single speaker in order to achieve reasonable performance. In practice, these speaker dependent (SD) systems are disadvantageous as large amounts of training data have to be collected and transcribed for each speaker, an approach only feasible for select applications.

The HMM based framework was shown to cope with variability as long as it has been observed in the training data. This allowed the construction of so-called speaker independent (SI) model sets where the HMMs are simply trained on data from multiple speakers. Recognition of utterances from any speaker are then produced with the same models. While this approach is much more practical the performance of an SI system is substantially inferior to an SD system trained on identical amounts of training data. Hence alternatives are required to bridge the gap. Human listeners are capable of adjusting to a new environment or speaker within a few words or sentences. Similarly for ASR, a few sentences can be used to adjust the models for recognition in order to yield better performance either in a second pass of recognition or for further sentences spoken by the target speaker.

Adaptation techniques can be classified in several ways: whether the acoustic models are changed or the extracted features or both (model- or feature-based adaption); whether changes to the models are made prior to adaptation (adaptation or normalisation); whether the labels used in adaptation can be assumed to be ground truth or with errors (supervised versus unsupervised adaptation). When the features are changed alone the changes to speech recognition accuracy are normally small and hence such methods are often preferred. However, it turns out that in most cases changes to the features work best when changing the acoustic models at the same time, referred to as normalisation. For most practical applications the ground truth is not known in which case the adaptation technique must be able to cope with potentially high levels of word error rate. This has a particularly bad effect on discriminative adaptation techniques (Gibson, 2008; Gibson & Hain, 2007; Wang & Woodland, 2002), however one effect usually alleviates that shortcoming: Recognition errors are often phonetically similar to the correct word. The phoneme error rate is often lower than the word error rate (Mangu *et al.*, 1999) and hence the correct models may still be chosen.

Since SD performance is assumed to be the best that can be obtained, an initial strategy is to first cluster speaker specific models into distinct groups. Then the adaptation step would simply consist of finding the most likely group and use the associated model for decoding. Albeit capable of producing SD performance in the limit it does not make good use of training data as speaker cluster models are only trained on data of a subgroup and disregarded for the rest. A better approach is provided by the so-called eigenvoices method (Kuhn *et al.*, 1998) where the principal components of the parameters of speaker cluster models (the means only are used in the original work) are found. Adaptation is performed by constructing models by weighted combination of these principal components. The weights are found by maximum likelihood optimisation on test data.

Another option to bridge the gap between SI and SD model performance is based on the estimation of a prior distribution over the model parameters. The speaker independent models are used to provide the prior. Maximum a Posteriori (MAP) adaptation (Gauvain & Lee, 1994) describes the updates of Gaussian (SI) means by data observed in adaptation:

$$\hat{\boldsymbol{\mu}} = \frac{\tau \boldsymbol{\mu}_{\text{prior}} + \sum_{t=1}^{T} \gamma_t \mathbf{x}_t}{\tau + \sum_{t=1}^{T} \gamma_t}$$

The new mean vector $\hat{\boldsymbol{\mu}}$ is changed from the old $\boldsymbol{\mu}_{\text{prior}}$ with the average observation vector $\mathbf{x}_t$, weighted by the posterior probability that the vector has been produced by this Gaussian. The factor τ can be selected to reflect the speed of adaptation and in practise iterative application of the above rules shows the best performance (Hain *et al.*, 2005a). While MAP adaptation can yield very good improvements it requires relatively large amounts of adaptation data to ensure that enough Gaussians have actually been observed and changed in the process. Discriminative versions of MAP exist to work with prior models that are already discriminatively trained (Povey *et al.*, 2003).

A more knowledge-driven approach is to target the physical differences between speakers, in particular the vocal tract shape and size, with the latter being the most distinctive feature (e.g. male/female vocal tract sizes differ substantially due the relative descent of the larynx in males during puberty (Harries *et al.*, 1998). The standard model of speech production is the source-filter model (Fant, 1960) and with a vocal tract filter represented by linear prediction based on autocorrelation. Here the vocal tract is represented as an ideal acoustic tube with varying length. Change to the length of the tube can be interpreted as a simple shift of the magnitude spectrum with short lengths associated with a more compact spectrum (Hain *et al.*, 1999; Cohen *et al.*, 1995). Vocal tract length normalisation (VTLN) implements the so-called warping of the frequency spectrum by shifting the Mel filter banks in MFCC or PLP feature extraction, subject to ensuring proper computation at boundaries (Hain *et al.*, 1999). Furthermore the optimal warp factor can be found by searching for the factor that yields the highest likelihood given a HMM set (Hain *et al.*, 1999). However, an SI model set would have been trained on speakers with different vocal tract lengths, increasing the variance of the distributions, an issue that can be avoided by training on normalised speaker data. Since maximum likelihood estimation is used to find the warp factors, models are trained iteratively, interleaving warp factor estimation and model training.

As outlined above VTLN targets the length of the vocal tract only, allowing the estimation of a single parameter per speaker. This was shown to be equivalent to multiplying the vectors with a matrix of specific structure (Claes *et al.*, 1998). The idea of multiplication with a matrix without constraints leads to one of the most important techniques in speaker adaptation, maximum likelihood linear regression (MLLR) (Leggetter & Woodland, 1995). Here the means are adjusted using a linear transform parameterised by a matrix $\mathbf{A}$ and a bias vector $\mathbf{b}$.

$$\hat{\boldsymbol{\mu}}_j = \mathbf{A}_{m(j)}\boldsymbol{\mu}_j + \mathbf{b}_{n(j)}$$

The major difference to MAP adaptation is that the update of the mean of the jth component can use a matrix which is shared across many Gaussian distributions, selected by the index functions $m(j)$and $n(j)$. These functions can be manually set or automatically found similar to techniques used in triphone state clustering (see Section 2.3). The matrices can be found by maximising the likelihood of test data using the transformed models. MLLR adaptation is very flexible as the structure of the matrices and vectors can be arbitrarily chosen (e.g. using diagonal transforms only). Variance adaptation is equally possible (Gales & Woodland, 1996) and joint optimisation with a common transform leads to constrained MLLR which can be implemented as a feature transform, thus again showing a connection with VTLN. As for VTLN, training on the normalised models also improves accuracy: Speaker adaptive training can be implemented with constrained MLLR or normal MLLR (Anastasakos *et al.*, 1996).

Speaker adaptation is a rich and extensive topic in automatic speech recognition and the space here is too small to give a full and in-depth account. Many valuable refinements have been made to the fundamental techniques above and some of the newer schemes have not been mentioned. The interested reader will find a good review by Woodland (2001).

3 Search

Given an observed sequence of acoustic feature vectors $\mathbf{X}$, and a set of HMMs, what is the most probable sequence of words $\hat{\mathbf{W}}$? This is referred to as the *search* or *decoding* problem, and involves performing the maximisation of equations (1–4). Since words are composed of HMM state sequences, we may express this criterion by summing over all state sequences $\mathbf{Q} = q_1, q_2, \ldots, q_n$, noting that the acoustic observation sequence is conditionally independent of the word sequence given the HMM state sequence. If we wish to obtain only the most probably state sequence, then we employ the *Viterbi* criterion, by maximising over $\mathcal{Q}_{\mathbf{W}}$, the set of all state sequences corresponding to word sequence $\mathbf{W}$:

$$\hat{\mathbf{W}} = \arg\max_{\mathbf{W}} P(\mathbf{W}) \max_{\mathbf{Q}\in\mathcal{Q}_{\mathbf{W}}} P(\mathbf{Q} \mid \mathbf{W}) P(\mathbf{X} \mid \mathbf{Q}) \tag{12}$$

Thus a decoding algorithm is required to determine $\hat{\mathbf{W}}$ using the above equation and the acoustic and language models.

Solving (12) by naive exhaustive search of all possible state sequences is of course not feasible. Viterbi decoding (forward dynamic programming) exploits the first-order Markov assumption to solve the problem efficiently. Given a state-time lattice, Viterbi decoding carries out a left-to-right time synchronous processing. This is structurally similar to the forward recursion (figure 4), except that the sum of probabilities of paths entering a state is replaced by a max operation. The Markov assumption is exploited by considering only the most probable path at each point in the state-time lattice: because the history is completely encapsulated by the current state, an extension to a lower probability path at a particular state-time location cannot become more probable than the same extension applied to the most probable path at that state-time location. Thus at each state-time point the single most probable path is retained, and the rest are discarded. The most probable path is the one at the end state at the final time.

To recognize a word sequence, a composite HMM for each word is built (including multiple pronunciations, if necessary) and a global HMM is constructed (figure 6). A bigram language model is easily incorporate, longer span models such as trigrams require a word history to be maintained. As mentioned in section 2.4, the acoustic model log likelihoods are often scaled by a factor $0 < \alpha < 1$, which takes into account the underestimate of the likelihood of an observation sequence arising from the conditional independence assumption.

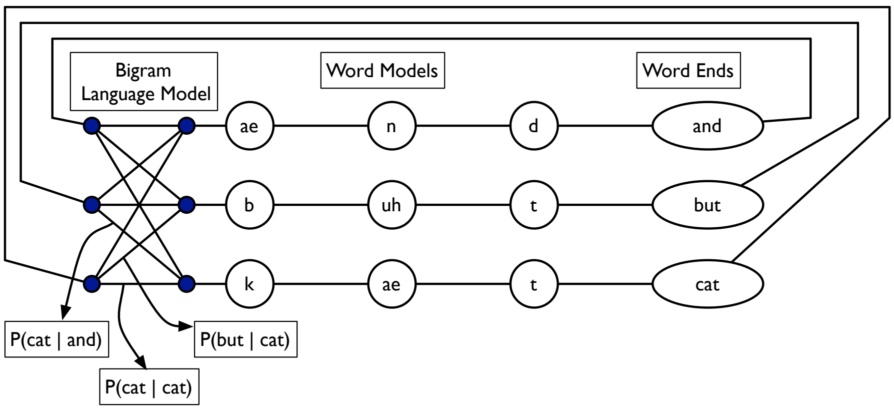


Figure 6. Connected word recognition with a bigram language model.

Viterbi decoding is an efficient, exact approach. However exact search is not usually possible for a large vocabulary task since the absence of predefined word boundaries means that any word in the vocabulary may start at each frame. Cross-word context-dependent triphone models and trigram language models add to the size of the search space and overall search complexity. Large vocabulary decoding must make the problem size more manageable by reducing the size of the search space through pruning unlikely hypotheses, eliminating repeated computations, or simplifying the acoustic or language models. A commonly employed approach to shared computation, which does not include approximation, arises from structuring the lexicon as a prefix pronunciation tree (Gupta *et al.*, 1988; Bahl *et al.*, 1993) in which common pronunciation prefixes are shared between word models; some extra book-keeping is required to take account of context-dependent word models (Ravishankar, 1996).

The most general approach to reducing the search space—and hence speeding up the decoding—is *beam search*. In beam search (Lowerre & Reddy, 1980; Ney & Ortmanns, 2000), unlikely search paths are pruned from the search, by removing modes in the time-state trellis whose path probability is more than a factor δ less probable then the best path, defining a beam of width δ. Both the acoustic and language models contribute to pruning in this way. Naively language models are applied at the end of a word, but it is possible to tighten the beam by applying a language model upper bound within the pronunciation tree. Applying beam search means that the decoding process is no longer exact, and hence increases in speed must be traded off against search errors—those errors that arise from incorrectly pruning a hypothesis that would go on to be the most probable. Some form of beam search is used in every large vocabulary decoder.

Most modern large vocabulary systems use a multi-pass search architecture (Austin *et al.*, 1991), in which progressively more detailed acoustic and language models are employed—the AMI system, described in section 4, is a good example of such a system. In multi-pass systems the search space is constrained by constructing word graphs (Ney & Ortmanns, 2000) with less detailed models, which are then rescored by more detailed models. Such a system can also be used to combine differently trained models.

In the 1990s most approaches to large vocabulary decoding constructed the search network dynamically. For a large vocabulary system, with a trigram language model, constructing the complete network in a static manner seemed out of the question in terms of required memory resources. Several very efficient dynamic search space decoders were designed and implemented (e.g. Odell, 1995). Although such decoders can be very resource effcient, they result in complex software with a tight interaction between the pruning algorithms and data structures. In contrast, searching a static network offers the ability to decouple search network construction from decoding, and to enable algorithms to optimize the network to be deployed in advance. Mohri and colleagues (Mohri *et al.*, 2000, 2002) have developed an approach to efficient static network construction based on weighted finite state transducer (WFST) theory. In this approach the components of the speech recognition system (acoustic models, pronunciations, language model) may be composed into a single decoding network, which is optimized using determinization and minimization procedures. This can result in a static network of manageable size, although the construction process may be memory intensive. Such WFST approaches have now been used successfully in several systems. A number of freely available toolkits for WFST manipulation now exist[8].

An alternative approach to large vocabulary decoding is based on heuristic search: *stack decoding* (Jelinek, 1969; Gopalakrishnan *et al.*, 1995; Renals & Hochberg, 1999). In stack decoding (which is essentially an A*-search), a

[8] WFST software: `http://www.openfst.org/`; `http://people.csail.mit.edu/ilh/fst/`; `http://www.research.att.com/~fsmtools/fsm/`

"stack" (prioriry queue) of partial hypotheses is constructed, with each hypothesis scored using the probability of decoding to the current time point, plus an estimate of the remaining score. In this time-asynchronous approach to decoding, a best-first approach is adopted. Since it does not rely on construction of a finite-state network it is well–suited to long-span language models and acoustic models.

4 Case study: The AMI system

Large vocabulary speech recognition systems have been developed for a number of applications, using the acoustic modelling framework outlined in the previous sections. In the research community the most notable examples include systems to recognise read newspaper text, broadcast news and conversational telephone speech. As discussed in section 1, read or planned speech has less variability than conversational or spontaneous speech, and this is reflected in the much lower word error rates obtained by automatic speech recognition systems on planned speech tasks. For both planned and spontaneous speech, it has been found consistently that the accuracy of an HMM-based speech recognition system is heavily dependent on the training data. This dependence has two main characteristics: First, accuracy increases as the amount of training data increases (experience has shown the relationship to be logarithmic). Second, the availability of transcribed, in-domain acoustic data for training of acoustic and language models leads to significantly reduced errors. Word error rates can be halved compared with models that were trained on data recorded under different conditions, or from a different task domain.

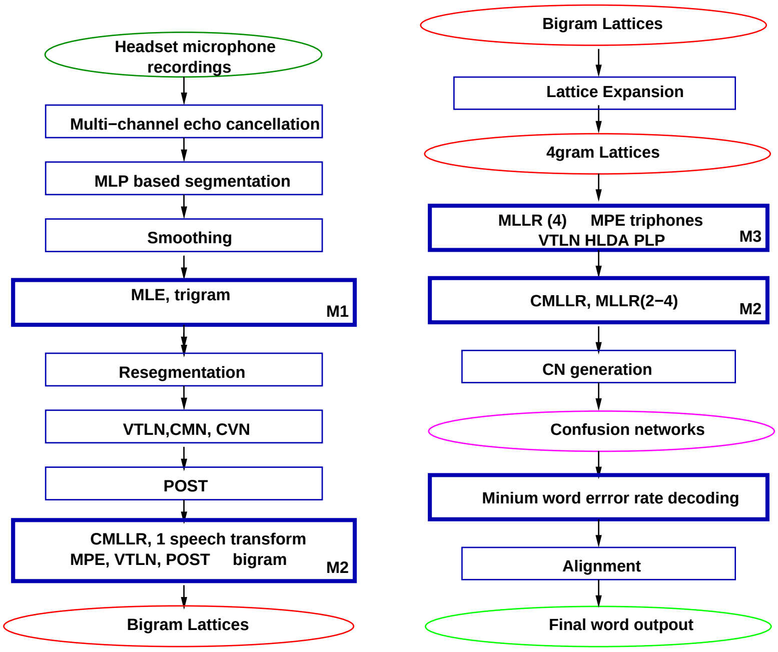
In this section we consider the construction of a speech recognition system for multiparty meetings. Multiparty meetings form a challenging task for speech recognition, characterised by spontaneous, conversational speech, with speech from different talkers overlapping. Since much of the work in this area has taken place in the context of the development of interactive environments, the data has been collected using both individual head-mounted microphones, as well as multiple microphones placed on a meeting room table (typically in some form of array configuration). Here we give a basic description of a system developed for the automatic transcription of meeting speech using head-mounted microphones; the system we outline was developed for the NIST Rich Transcription evaluation in 2006, and some of the final system's complexity has been omitted for clarity.

The meetings domain forms an excellent platform for speech recognition research. Important research issues, necessary to the construction of an accurate system for meeting recognition include segmentation into utterances by talker, robustness to noise and reverberation, algorithms to exploit multiple microphone recordings, multi-pass decoding strategies to enable the incorporation of more detailed acoustic and language models, and the use of system combination and cross-adaptation strategies to exploit system complementarity. The exploitation of system complementarity has proven to have a significant effect on word error rates. Speech recognition architectures may differ in terms of training data, features or model topology, and these differences can result in systematically different errors. One can capitalise on such differences in two ways. First, unsupervised cross-adaptation enables the output of one part of the system to adapt another different part. This enables some of the adverse effects caused by unsupervised adaptation to be alleviated. Second, system combination allows the combination of the outputs of several stages of a system, for example by use of majority voting (Fiscus, 1997).

Work on meeting transcription has in part been dominated by the fact that the amount of in-domain data is usually relatively small. As for any other spontaneous speech source, the cost of manual transcription is high (manual transcription of meeting data is about 25 times slower than real-time). For the system described here, about 100 hours of acoustic training data from meetings were available which is still modest. Hence most systems make use of adaptation of models from other domains. Stolcke *et al.* (2004)

used a recognition system for conversational telephone speech as the starting point (others have reported that starting from Broadcast News systems also works well, e.g. Schultz *et al.* (2004)) and we have followed that strategy. Our experiments with language models for meeting data (Hain *et al.*, 2005b) indicated that the vocabulary is similar to that used for broadcast news, with only a few additional out-of-vocabulary words. Later work has shown that meeting-specific language models can give lower perplexity and word error rate, but the effect is small. Our systems have used a vocabulary of 50 000 words based on the contents of meeting transcriptions augmented with the most frequent words from broadcast news. Pronunciations were based on the UNISYN dictionary (Fitt, 2000). The baseline language model for these experiments was a trigram built using the meeting transcripts, a substantial amount of broadcast news data and most importantly data collected from the Internet obtained by queries constructed from n-grams in the meeting transcripts (Bulyko *et al.*, 2003; Wan & Hain, 2006).

Figure 7 presents an overall schematic of the meeting transcription system. The initial three steps preprocess the raw recordings into segmented utterances suitable for processing by the recognizer. A least mean squares echo canceller (Messerschmitt *et al.*, 1989) is applied to alleviate cross-talk in overlapped speech, followed by an automatic segmentation into speech utterances. The segmentation was performed on a per-channel basis, and in addition to using the standard speech recognition features (PLP features in this case) a number of other acoustic features are used including cross-channel normalised energy, signal kurtosis, mean cross-correlation and maximum normalised cross-correlation (Wrigley *et al.*, 2005; Dines *et al.*, 2006). The segmentation is based on a multi-layer perceptron trained on 90 hours of meeting



(a) Initial lattice generation

(b) Cross-adaptation and CN decoding

Figure 7. Block processing diagram showing the AMI 2006 system for meeting transcriptionHain *et al.* (2006). Square boxes denote processing steps, bold boxes denote generation of word output, ellipses representations of the data. M1-M3 denote differently trained model sets.

data. This exceptionally large amount of training data for a simple binary classification was necessary to yield good performance. The raw segment output is then smoothed in order to mirror the segmentation used in training of acoustic models.

The initial acoustic models were then trained using features obtained from a 12th order MF-PLP feature analysis, plus energy. First and second temporal derivatives are estimated and appended to the feature vector, resulting in 39-dimension feature vectors, which are then normalised on a per channel basis to zero mean and unit variance (cepstral mean and variance normalisation).

After these audio preparation stages 39 dimensional MF-PLP feature vectors are extracted and cepstral mean and variance normalisation (CMN/CVN) was performed on a per channel basis. Then first pass transcripts are produced, using models trained on 100 hours of meeting data (M1) and a trigram language model. This initial transcript has several uses, including the provision of a rough transcript for estimation of VTLN warp factors, and to allow the data to be re-segmented by re-aligning to the transcripts. This is possible because the acoustic models for recognition are more refined than the models used for segmentation, but naturally segments can only get shorter. This is important as cepstral mean and variance normalisation have a significant impact on word error rate and rely on the correct balance of silence in segments.

The next pass of decoding uses different features than before. The standard PLP feature vector is augmented with phone-state posterior probabilities computed using a multi-layer perceptrons (further details can be found in Section 5) and both components are normalised using VTLN. Acoustic models are now trained using the MPE criterion (Section 2.4) and further adapted using a single CMLLR transform (Section 2.5). As the system has more passes to follow, bigram lattices are produced at this stage in order to enable lattice rescoring using new acoustic and language models. If a faster system was required, decoding with a trigram as the in the first pass could have been chosen here.

The second part of the system, figure 7(b), follows the strategy of using a constrained search space as represented in a lattice to quickly obtain improvements and apply models that could otherwise not be used. First a 4-gram language model (trained on the same data as those before) is used to expand lattices and producing a new first-best output). This is followed by decoding with two different acoustic model sets for the purpose of cross-adaptation. The first acoustic model set uses standard PLP feature only but models are trained by MAP adaptation from 300 hours of conversational data. After adaptation with MLLR again, lattices are produced that are rescored using the same models and features as in the second pass. Finally lattices are compacted in the form of confusion networks and minimum word error rate decoding is performed. Final alignment is only performed to find correct times for words.

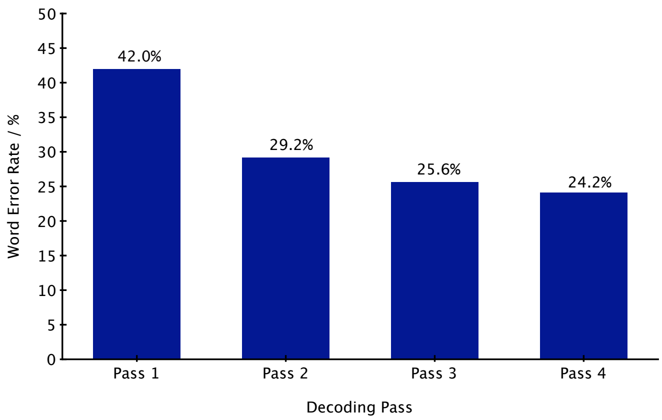


Figure 8. Word error rates (%) results in the NIST RT'06 evaluations of the AMI 2006 system on the evaluation test set, for the four decoding passes as shown in figure 12.7.

Figure 8 shows results for all passes. If the initial automatic segmentation into utterances is replaced by a manual process, then the word error rate is decreased by 2–3% absolute. Considerable reductions of word error rates are achieved in each pass. Note that the first pass error rate is almost twice the error rate of the final pass, but the processes of adaptation and normalization in the second pass account for most of the gain. Even though the second pass uses the same acoustic models as the final pass, cross-adaptation still brings an additional 2.4% in word error rate.

5 Current topics

5.1 Robustness

The early commercial successes of speech recognition, for example dictation software, assumed that the speech to be recognized was spoken in a quiet, non-reverberant environment. However most speech communication occurs in less constrained environments characterised by multiple acoustic sources, unknown room acoustics, overlapping talkers and unknown microphones.

A first approach to dealing with additive noise is by using multiple microphones to capture the speech. Microphone array beamforming uses delay-sum or filter-sum techniques to offer a gain in specific directions, thus enabling competing acoustic sources to be separated based on location (Elko & Meyer, 2008). These approaches have been used successfully in meeting transcription systems; using beamformed output of a microphone array will increase the word error rate by about 5% in the case of limited overlapping speech (Renals *et al.*, 2008), by up to 10% in more general situations, compared with using close-talking microphones.

Most work in robust speech recognition has focused on the development of models and algorithms for a single audio channel.[9] Increased additive noise will cause the word error rate of a speech recogniser trained in clean, noise-free conditions to increase rapidly. For the Aurora-2 task of continuously spoken digits with differing levels of artificially added noise, the case of clean test data will result in word error rates of less than 0.5% using acoustic models trained on clean speech. A very low level of added noise (20 dB SNR—signal-to-noise ratio) results in ten times more errors (5% word error rate) and equal

[9] This is a general case, since microphone array beamforming will result in a single audio channel.

amounts of noise and speech (0 dB SNR) results in a word error rate of about 85% (Droppo & Acero, 2008). Thus the noise problem in speech recognition is significant indeed.

The reason for the dramatic drop in accuracy is related to acoustic mismatch; the noisy test data is no longer well matched to the models trained on clean speech. If we knew that the noise would be of a particular type (say car noise) and at a particular level (say 10 dB SNR) then we could artificially create well-matched training data and retrain a set of matched noisy models. However it is rarely the case that the test noise conditions are known in such detail. In such cases multistyle training can be employed, in which the training data is duplicated and different types of noise added at different SNRs. This can be very effective: in the previous Aurora task, multistyle training decreases the 20 dB SNR word error rate from 5% to about 1%, and the 0 dB word error rate from 85% to 34%, while adding about 0.1% to the clean speech error rate (Droppo & Acero, 2008). Multistyle training is thus very effective, but it is rather computationally expensive: it may be feasible for training a recogniser on digit strings (a task with an 11 word vocabulary), it is much less feasible for conversational speech recognition. Indeed, most of the techniques discussed in what follows have been developed largely on relatively small vocabulary tasks.

Beyond the brute force approach of multistyle training, there are two main approaches to robustness: feature compensation and model compensation. The aim of feature compensation is to transform the observed noisy speech into a signal that is more closely matched to the clean speech on which the models were trained. It is usually of interest to develop techniques that work in the cepstral feature domain, since speech recognition feature vectors are usually based on PLP or Mel frequency cepstral coefficients. Cepstral mean and variance normalisation (CMN/CVN) is a commonly applied technique which involves normalising the feature vectors, on a component-by-component basis, to zero mean and unit variance. CMN can be interpreted in terms of making the features robust to linear filtering such as that arising from varying type or position of microphones, or characteristics of a telephone channel. For both the Aurora digits task and for large vocabulary conversational telephone speech recognition, CMN and CVN can reduce word error rates by 2–3% absolute (Droppo & Acero, 2008; Garau & Renals, 2008).

More elaborate forms of feature normalisation attempt to directly transform recorded noisy speech to speech that matches the trained models. One technique, designed primarily for stationary noise, is spectral subtraction, in which an estimate is made of the noise (in spectral domain), and subtracted from the noisy speech, to (theoretically) leave just clean speech (Lockwood & Boudy, 1992). The subtraction process may be nonlinear and dependent on the SNR estimate. This technique requires good segmentation of speech from non–speech in order to estimate the noise. If that is possible the technique works well in practice The *ETSI Advanced Front End* for noisy speech recognition over cellular phones is based on CMN and spectral subtraction and can reduce errors from 9.9% to 6.8% on a multistyle trained Aurora-2 systems (Macho *et al.*, 2002).

Spectral subtraction may be regarded as a very simple noisy-to-clean mapping, that simply subtracts an estimate of the average noise. More sophisticated approaches are available, for example SPLICE which is based on the estimation of a parameterised model of the joint density of the clean and noisy speech (Deng *et al.*, 2000). A Gaussian mixture model is typically used, and stereo data containing parallel clean and noisy recordings of the same signal is required for training. Other approaches to feature compensation include missing feature models (Cooke *et al.*, 2001) and uncertainty decoding (Droppo *et al.*, 2002) in which areas of time-frequency space are attributed to speech or noise, and probabilistic enhancement approaches are used to reconstruct the clean speech.

It is also possible to use model-based compensation, in which the detailed acoustic models in the recogniser are used as the basis of the compensation scheme, as opposed to the previous approaches which construct specific feature compensation models. In model-based compensation the clean speech models are combined with a noise model, resulting in a model of noisy speech. This is referred to parallel model combination (Gales & Young, 1996) . There are two main technical challenges with parallel model combination. First, noise models that are more complex than a single state result in much greater complexity overall, due the fact that the speech and noise models are combined as a product. Second, it assumed that speech and noise are additive in the spectral domain. Since the models are constructed in the cepstral domain, it is necessary to transform the model parameters (Gaussian means and covariances) from the cepstral to the spectral domain. The noisy speech model statistics are then computed in spectral domain, before transforming the parameters back to the cepstral domain.

5.2 Multiple knowledge sources

It is possible obtain many different parameterisations of the speech signal and to use different acoustic model formulations. Often different representations and models result in different strengths and weaknesses, leading to systems which make complementary errors. It is possible that word error rates could be reduced if such systems are combined.

In feature combination approaches, multiple different feature vectors are computed at each frame, then combined. Although the most commonly employed acoustic parameterisations such as MFCCs and PLP cepstral coefficients result in low error rates, on the average, it has been found that combining them with other representations of the speech signal can lower word error rates. For example, Garau & Renals (2008) combined MFCC and PLP features with features derived from the pitch-adaptive STRAIGHT spectral representation (Kawahara *et al.*, 1999), and Schlueter *et al.* (2007) combined MFCC and PLP features with gammatone features derived from an auditory-inspired filterbank, each time demonstrating a reduction in word error rate.

The simplest way to combine multiple feature vectors is simply to concatenate them at each frame. This is far from optimal since it can increase the dimensionality quite substantially, as well resulting in feature vectors with strong dependences between their elements. The latter effect can cause numerical problems when estimating covariance matrices. To avoid these problems, the feature vectors may be concatenated, then linearly transformed to both reduce dimensionality and decorrelate the components. Although principal component analysis is one way to accomplish this, it has been found that methods based on linear discriminant analysis (LDA) are preferable, since a different transform may be derived for each state. Hunt proposed the use of LDA to improve discrimination between syllables, and in later work used LDA to combine feature streams from an auditory model front end (Hunt & Lefebvre, 1988). In LDA a linear transform is found that maximises the between class covariance, while minimising the within class covariance. LDA makes two assumptions: first, all the classes follow a multivariate Gaussian distribution; second, they share the same within-class covariance matrix. Heteroscedatic LDA (Kumar & Andreou, 1998) relaxes the second assumption and may be considered as a generalisation of LDA.

As discussed further in section 5.3, other feature representations have been explored, which have a less direct link to the acoustics. For example, considerable success has been achieved using Tandem representations in which acoustic features such as MFCCs are combined with frame-wise estimates of phone posterior probabilities, computed using multi-layer perceptrons (MLPs). An advantage of this approach is that the MLP-based phone probability estimation can be obtained using a large amount of temporal context.

Other levels of combination are possible. Acoustic models may be combined using the combining probability estimates at the frame or at the segment level. Approaches such as ROVER (Fiscus, 1997) enable system-level combination in which multiple transcriptions , each produced by a different system, may be combined using a dynamic programming search based on majority voting or on confidence scores. Such approaches have been used to great effect in recent large scale research systems and are discussed further in section 5.4.

5.3 Richer sequence models

One of the main weaknesses of HMM based speech recognition is the assumption of conditional independence of speech samples, i.e.

$$p(\mathbf{x}_t|\mathbf{x}_1 \ldots \mathbf{x}_{t-1}, q_t) \equiv p(\mathbf{x}_t|q_t),$$

where q_t denotes the current state and $\mathbf{x}_t$ denotes the acoustic vector at time t. The conditional independence assumption is incorrect, since it fails to reflect the strong constraints in the speed of movement of articulators, that adjacent frames have high correlation and changes in the spectrum are slow for most sound classes. Some interdependence is of course encoded in the state succession but transition probabilities only exist from one state to the next and are usually found to have modest influence on performance. This leads to considerable under-estimation of true frame likelihoods and two approaches or commonly used to counteract that: the use of differentials (so-called delta features) in the feature vector to account for slope information; and scaling of the language model probabilities in decoding and also training to adjust for dynamic range differences. However, these changes are engineering solutions without a solid theoretical base and also account for part of the shortcoming.

There have been many attempts to address the issue and we cannot present all of those attempted over the years. However, recently interest in better modelling of the temporal modelling of parameters has increased and considerable improvements have been obtained with some techniques. Sometimes results are difficult to interpret because they include multiple changes to the systems and hence multiple interpretations of the realisation is possible. In general all of the techniques are much more computationally elaborate and some are so complex that only rough approximations to the formulae make it possible to realise such structures. Even with modern large scale computing resources proper implementations are not possible.

Segment models were introduced by Ostendorf & Roukos (1989) and interpreted as an extension to HMM based modelling (Ostendorf *et al.*, 1996). Instead of modelling single frames multiple frames can be represented at the same time, for example by describing a moving mean of a Gaussian distribution. Similar to HMMs one can represent states associated with segments that have variable length. The question on length of the segments and their proper representation in functional form was and still is the topic of investigation, however the techniques have not found entry into large scale systems partially due to complexity reasons.

One of the issues pointed out by Tokuda *et al.* (2000) in the context of HMM based speech synthesis is the incorrect use of Gaussians for differentials of the static features, noting that an implicit continuity constraint is missing. A formulation that adds this constraint to a standard HMMs for recognition is given in (Zen *et al.*, 2007a). In experiments significant improvements in word error rates have been observed in some simple tasks, but these improvements have not been observed in more complex tasks (Zhang & Renals, 2006).

A much simpler and very effective method has been introduced in the form of the so-called TRAPS features (Sharma *et al.*, 2000) which since then have been implemented in several large scale systems in many different applications and modified forms (e.g. the AMI system as presented in Section 4 uses so called LC/RC features as described by Schwarz *et al.* (2004)). The basic idea is to convert long term information into a single feature vector that is capable of extracting relevant information at the given time. Long-term information can cover up to half a second but most techniques make use of information compression by use of e.g. a KLT transform on a frequency band basis. The compressed information is then filtered through a multi-layer perceptron that is trained to map features to phoneme state level posterior probabilities. This step is vital as it allows to construct a feature vector that is relevant to the current time without causing information diffusion. Such features can be combined with standard features but recent results seem to suggest that the potential loss in performance is small when used on their own. Substantial improvements are obtained on small and large scale tasks and gains are often complimentary with other techniques.

This technique bears a strong relationship with another technique aimed at augmenting feature vectors. fMPE (Povey *et al.*, 2005) or feature based MPE training tries to find a matrix $\mathbf{M}$ such that a new feature vector $\mathbf{y}_t$ is more informative:

$$\mathbf{y}_t = \mathbf{x}_t + \mathbf{M}\mathbf{h}_t$$

This is achieved by providing additional information on neighbouring frames to the current time in the form of a vector $\mathbf{h}_t$ but instead of using the features directly their projection into the model space is performed by using their likelihood for each Gaussian in the acoustic model set, thus providing a link to the models. The matrix is then trained using the MPE type criterion function. Substantial improvements are obtained but training of models and matrices is complex and the application of the matrix in decoding is costly. Hifny & Renals (2009) introduced a related discriminative method, augmented conditional random fields.

Much more advanced approaches try to model long-term dynamics in a more principled form using for example switching linear dynamical systems (Digalakis *et al.*, 1993; Rosti & Gales, 2003). Here the fundamental assumption necessary for Viterbi approximation, the assumption that the preceding model does not have an influence on the current model, is normally not correct and hence search paths can not be merged. At this point for many situations only small scale experiments are possible and even then substantial constraints have to be included.

5.4 Large scale

Since the 1990s there has been an intense interest in developing approaches to speech recognition that work well in natural situations. In particular there has been a significant focus on conversational telephone speech, broadcast news and, more recently, multiparty meetings. Challenges for the recognition of conversational telephone speech include conversational style and the telephone channel. For broadcast news, the speech signals come from a variety of sources and are mixed with other sounds such as music or street noise. The meeting domain adds the challenge of far-field recording and reverberation to conversational speech recognition. Much of this work has been performed in US English, since resources in other languages are usually much more sparse. Lately increased interest in Mandarin and Arabic, as well as "international English", has lead to extensive resource generation in those languages. Work in different languages brings to the fore important aspects such as larger vocabularies (over 500 000 words) due to different morphologies, different error metrics, such as character error rate, ambiguity in orthographic and spoken word, or additional sound classes such as Mandarin tones. Remarkably the basic structure in most systems remain identical and changes are mostly made to dictionaries or feature extraction.

The increasing amounts of data as well as the additional acoustic and speech complexity have substantial implications for system building. Segmentation and speaker clustering optimal for speaker recognition or for playback, is normally not optimal for automatic speech recognition (Stolcke *et al.*, 2004). Multiple microphone sources can affect the best strategies for acoustic modelling and adaptation. Automatic switching between microphones causes potentially substantial errors (Hain *et al.*, 2008). Adapting models to the speaker and to the environment has proven to be extremely important, but the interaction between different model adaptations is complex. In particular, the order of application of techniques is important and may need changing depending on domain or data type.

Dependence on a domain, lack of generalisability is a major challenge. Techniques known to work on one domain do not necessarily work on another domain: this has been observed for VTLN, (Kim *et al.*, 2004), for instance. If the in-domain data is sparse, then improved accuracy can be obtained by adaptation from large corpora in related domains. This may requite compensation techniques for mismatch between domains; an example of this is the approach of Karafiat *et al.* (2007) to compensate for different audio bandwidths. Finally the appropriate evaluation metric may be domain-specific. Word error rate is not the only metric, and optimising systems for specific applications, such as machine translation (Gales *et al.*, 2007) can lead to significant improvements.

The above illustrates that an almost limitless range of options for system building exists which can serve two fundamentally different purposes: to enhance system performance in one application by finding combinations of components that can enhance each others performance; or to find the components that will yield the perfect result for a particular element of data. Only limited work has been carried out on the latter, but investigations on the AMI RT'07 system (Hain *et al.*, 2007b) show that the oracle combination of outputs of various stages of a system can yield 20% relative reduction in word error rate.

With the more widespread use of high level system combination (Fiscus, 1997; Evermann & Woodland, 2000) recognition systems became more complex. While attempts were made to describe generic all-purpose system architectures (Evermann & Woodland, 2003) experience showed that the search for complimentary systems may allow for much simpler structures (Schwartz *et al.*, 2004) where in essence the output of one systems is simply used to adapt another one and then the respective outputs are combined. Nevertheless systems that differ by such a margin are difficult to construct. Hence more elaborate schemes such as in the SRI-ICSI or AMI RT'07 systems (Stolcke *et al.*, 2007; Hain *et al.*, 2007b) are developed. In these cases acoustic modelling, segmentation and data representation is varied to yield complementarity.

The challenges for system development in the future are defined in the list of requirements above. Since the complexity of systems is set to increase rather than decrease a manual construction of system designs will always be sub-optimal. In (Hain *et al.*, 2008) initial attempts are reported for automation of system design. However, at this point even the right form to describe the potential combinations efficiently is unknown, let alone a multi-objective dynamic optimisation scheme. To find optimal systems not only optimal combination and processing order has to be derived, ideally the models and techniques are complimentary and yield mutually additive gains. Approaches have been made to automate this process (e.g. Breslin & Gales (2006)) but much more work is required, in particular in the context of different target metrics.

6 Conclusions

Automatic speech recognition was one of the first areas in which the data-driven, machine learning, statistical modelling approach became standard. Over the past two decades the basic approach has been developed in several important ways. Detailed models of speech may be constructed from training data, with the level of modelling detail specified by the data. Algorithms to adapt these detailed models to a specific speaker have been developed, even when only a small amount of speaker-specific data is available. Discriminative training methods, which optimize the word error rate directly, have been developed and used successfully. Because of these successful strategies speech recognition is available in commercial products in many forms. Public perception of speech recognition technology however ranges widely, from "solved" to "hopeless". The reasons for the mixed acceptance lie in number of major challenges for speech recognition that are still open today. First, speech recognition systems can only operate in a much more limited set of conditions, compared with people: additive noise, reverberation, and overlapping talkers pose major problems to current systems. Second, the integration of higher level information is weak and often non-existent albeit being of obvious use to humans. Third, current models of speech recognition have a rather weak temporal model. The use of richer temporal models has had an inconsistent impact on the word error rate. Finally systems lack generalizability: they are very dependent on matched training data. Moving a system from one domain to another, without training data resources for the new domain will result in a greatly increased word error rate.

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