Multilingual man-machine communication

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1 Overview

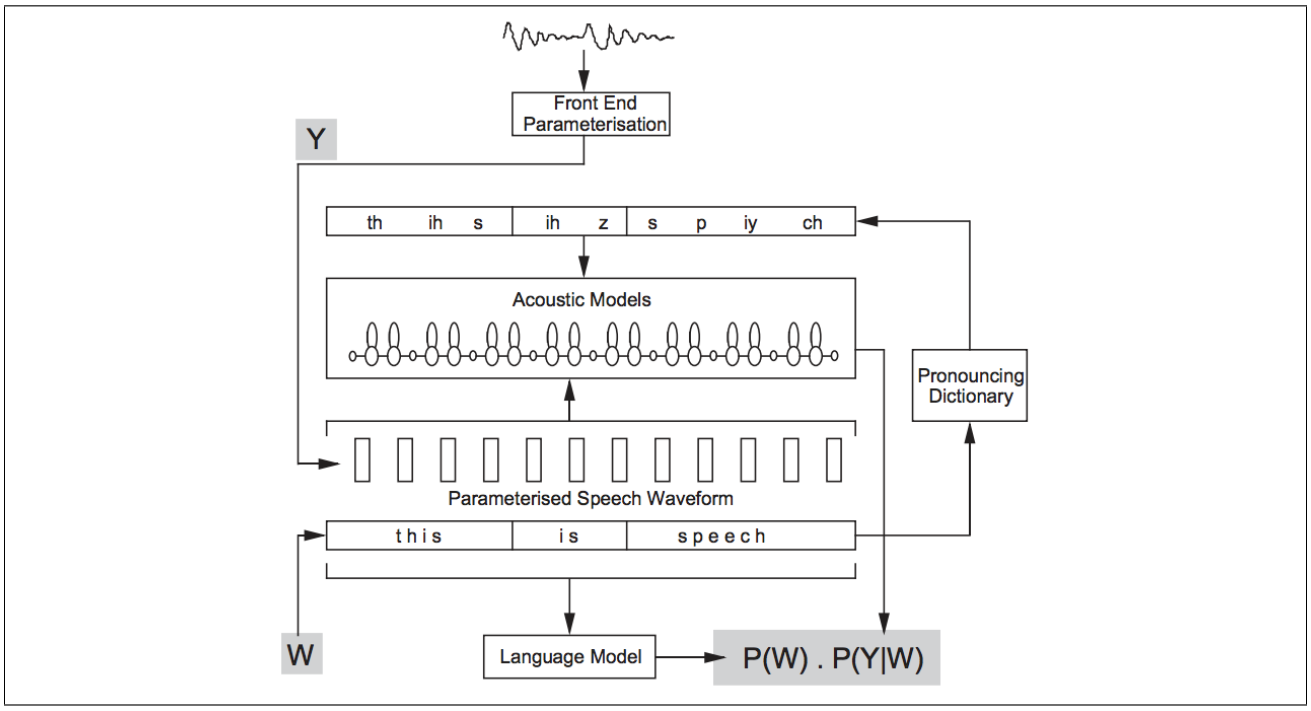


Figure 1: Overview according to Young

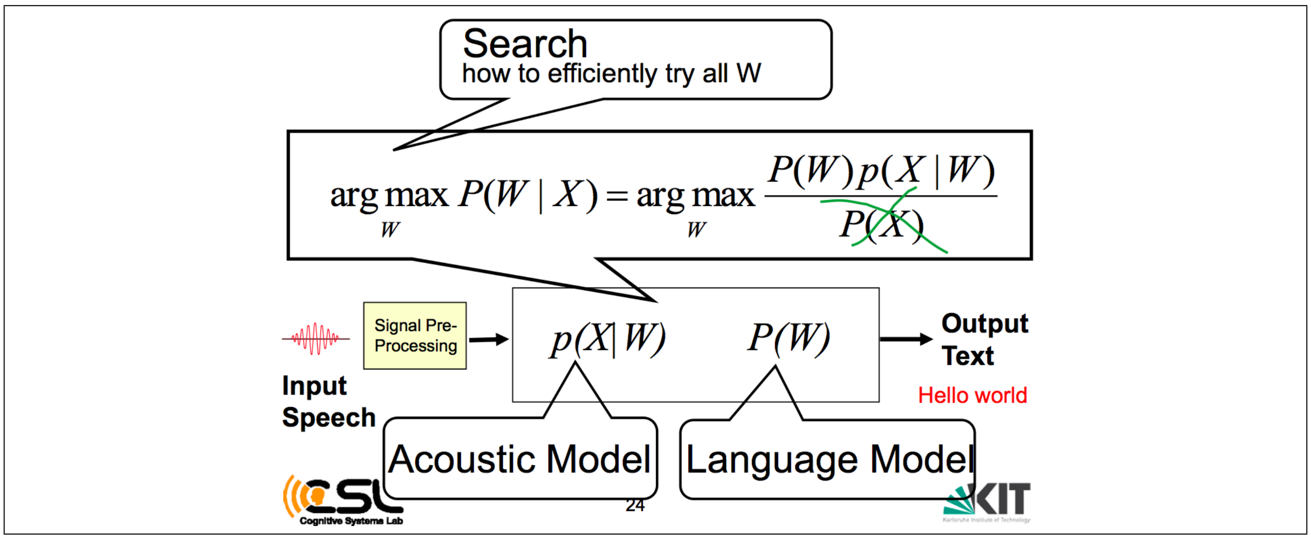
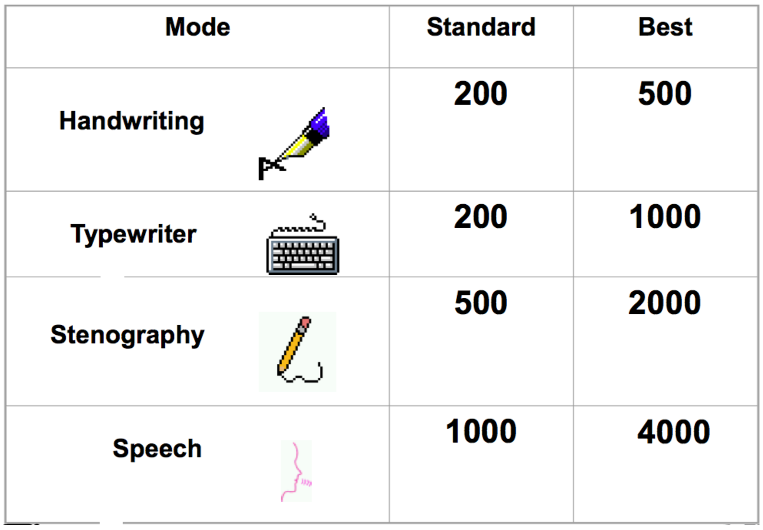


Figure 2: Overview according to Schultz

2 Introduction

2.1 Why do we need Automatic Speech Recognition (ASR)?

Advantages	Disadvantages
Speech is a natural way of communication	When you are not allowed to speak, it is unusable
Allows an additional communication channel	Unsatisfactory recognition rate
Hands and eyes are free for other tasks	Problems with accents, dialects and code-switching
Mobility	Cultural factors (e.g. uncertainty avoidance)
Some communication channels are speech-only	Speech input is still more expensive



Mode	Standard	Best
Handwriting	200	500
Typewriter	200	1000
Stenography	500	2000
Speech	1000	4000

Figure 3: Input Characters per minute

2.2 Where is Speech Recognition and Understanding useful?

2.2.1 Human-Machine Interaction

1. Applications for Remote Control
    - Using the phone to operate machines
2. Hands/eyes are busy or not usable
    - Speech recognition while driving
    - Nurse bots for physically disabled
3. Authentication
    - Speaker Identification/Verification/Segmentation
    - Language/Accent Identification
4. Entertainment
5. Indexing and Transcribing Acoustic Documents
    - Archive, Summarize, Search and Data Retrieval

2.2.2 Human-Human Interaction

1. Communication across language barriers
   - Simultaniously translating one language into the other
2. Support human interaction
   - Meeting and lecture systems
   - Speech therapy support

3 Basics

3.1 Speech units

- **phone**: a sound one produces, such as [p]
- **phoneme**: an abstract unit, such as /h/
- **morpheme**: the smallest part of speech with semantic meaning, for example un-break-able

When the meaning of an utterance can be changed by replacing one phone in the utterance with another phone, the replaced phone and the phone that replaces it are said to form a **minimal pair**. A phoneme may correspond to one phone or a set of phones. In the latter case, all phones of the set are called **allophones** of the phoneme. For example, /o/ and /u/ are phonemes in English because there are minimal pairs that differ only in these phonemes, such as "bone" and "boon". The English phoneme /p/ has two allophones, one with aspiration and one without it.

3.2 k-means clustering

Given an observation $(x_1, \dots, x_n)$, find $k \leq n$ clusters $S = \{S_1, \dots, S_k\}$, such that:

$$\underset{S}{\operatorname{argmin}} \sum_{i=1}^{k} \sum_{x_j \in S_i} ||x_j - \mu_i||^2$$

where μ_i is the mean of points in S_i.

3.3 Comparing two utterances

- linear alignment
- dynamic time warping (DTW)

4 Signal processing

4.1 Short-Term Spectral Analysis

The general idea of short-term spectral analysis is to

- multiply the speech signal with a window function
- apply the Discrete Time Fourier Transform (DTFT)
- use a filterbank (such as *Mel* or *Bark*)

4.2 Linear Predictive Coding

LPC is an alternative to Fourier analysis. When using LPC, we assume that a speech signal is produced by a buzzer (*glottis*) at the end of a tube (*vocal tract*), with occasional added hissing and popping sounds. Then, the intensity and frequency can be estimated with linear prediction:

$$\tilde{s}(n) = \sum_{i=1}^{p} \alpha_i s(n-i) \tag{1}$$

Some sounds, for example nasal sounds, cannot be described by this model. This means that there will be an error, called the residue, which is stored and used to model other sounds:

$$e(n) = s(n) - \tilde{s}(n) \tag{2}$$

The goal of the prediction is to minimize the squared error $\sum e(n)^2$. This error can be further transformed into cepstral coefficients using the Z-transform.

4.3 Cepstra

The speech signal $s(n)$ can be described by a convolution of stimulating signal $u(n)$ (caused by the glottis) and an impulse response $h(n)$ (caused by the vocal tract and the lips):

$$s(n) = u(n) * h(n) \tag{3}$$

In speech analysis, we are particularly interested in discovering the formant structure. This means that we have to "get rid" of the stimulating signal:

$$\mathcal{F}(s) = \mathcal{F}(u) \cdot \mathcal{F}(h) \tag{4}$$

$$\mathcal{F}^{-1}(\log(\mathcal{F}(s))) = \mathcal{F}^{-1}(\log(\mathcal{F}(u))) + \mathcal{F}^{-1}(\log(\mathcal{F}(h))) \tag{5}$$

Note that after the inverse Fourier transform, we are not in the time domain, but in the cepstral domain. The lower cepstral coefficients describe the macro structure of the signal whereas the higher cepstral coefficients describe the micro structure of the signal. Thus, the higher cepstral coefficients are often discarded.
In order to separate the signal's components, we have to apply a *lifter* to filter out the information we need. This is done by removing cepstral summits with a lowpass lifter.

4.3.1 Mel-frequency cepstrum

MFCCs are coefficients that collectively make up an MFC. MFCCs are commonly derived as follows:

1. apply the Fourier transform to a signal
2. apply a Mel filterbank
3. take the log of the powers at each Mel "bucket"
4. take the discrete cosine transform (DCT) of the list of mel log powers
5. the MFCCs are the amplitudes of the resulting spectrum

Usually, we take the first coefficient (the power of the signal) and 12 more coefficients, amounting to a total of 13 numbers.

4.4 Feature vectors

During further processing, we often assume that the speech signal at a given point of time is independent from the signal before and after that point of time. This is a poor assumption. So, if we have a feature vector x (if we're using MFCCs, we have 13 coefficients), we also store the first and second derivatives of x, namely Δx and $\Delta\Delta x$ (if we're using MFCCs, we now have 39 numbers).

5 Hidden Markov Models

5.1 The three great problems

5.1.1 Evaluation

Problem: Given an HMM λ and an observation $O = (x_1, \ldots, x_T)$, compute the probability $P(x_1, \ldots, x_T|\lambda)$.

A weaker problem: Given an HMM λ an observation $O = (x_1, \ldots, x_T)$ and a state sequence $(s_{q_i}, \ldots, s_{q_T})$, compute the probability $P(x_1, \ldots, x_T|\lambda, (s_{q_1}, \ldots, s_{q_T}))$.

Solution:

$$\pi(s_{q_1})b_{q_1}(x_1)\prod_{k=1}^{T-1} a_{q_k q_{k+1}} b_{q_{k+1}}(x_{k+1}) \tag{6}$$

This solution is of course not applicable to the evaluation problem because the state sequence is unknown.

Solution: the Forward algorithm. Define:

$$\alpha_1(j) = \pi(s_j) \cdot b_j(x_1) \tag{7}$$

$$\alpha_t(j) = \sum_i a_{ij} \cdot \alpha_{t-1}(i) \tag{8}$$

5.1.2 Decoding

Problem: Given an HMM λ, and an observation $O = (x_1, \ldots, x_T)$, find the most likely state sequence $s_{q_1}, \ldots, s_{q_T}$:

$$\begin{aligned}
\underset{(q_1,\ldots,q_T)}{\operatorname{argmax}} P(q_1, \ldots, q_T \mid x_1, \ldots, x_T, \lambda) &= \underset{(q_1,\ldots,q_T)}{\operatorname{argmax}} \frac{P(q_1, \ldots, q_T, x_1, \ldots, x_T \mid \lambda)}{P(x_1, \ldots, x_T \mid \lambda)} \\
&= \underset{(q_1,\ldots,q_T)}{\operatorname{argmax}} P(q_1, \ldots, q_T, x_1, \ldots, x_T \mid \lambda)
\end{aligned}$$

Solution: the Viterbi algorithm. Define:

$$z_1(j) = \pi(j) \cdot b_j(x_1) \tag{9}$$

$$z_t(j) = \max_i(a_{ij} \cdot z_{t-1}(i)) \cdot b_j(x_t) \tag{10}$$

Both the Forward and the Viterbi algorithm often multiply many small numbers. This can lead to floating point underflow errors. As a solution, one can either scale the factor by a constant or use logarithms to turn the multiplications into additions.

5.1.3 The Backward algorithm

Obviously:

$$P(x_1, \dots, x_T \mid \lambda) = \sum_i P(x_1, \dots, x_T, q_t = i \mid \lambda) \tag{11}$$

Define:

$$\beta_t(i) = P(x_{t+1}, \dots, x_T, q_t = i \mid \lambda) \tag{12}$$

$\beta_t(i)$ is the probability of observing the partial observation $x_{t+1}, \dots, x_T$ and being in state s_i. Then:

1. Initialization: $\beta_T(i) = N^{-1}$
2. Induction: $\beta_t(i) = \sum\limits_j a_{ij} \cdot b_j(x_{t+1}) \cdot \beta_{t+1}(j)$
3. Termination: $P(x_1, \dots, x_T \mid \lambda) = \sum\limits_j \beta_T(j)$ (shouldn't this be $\sum\limits_j \beta_1(j)$?)

5.1.4 Learning / optimization

Goal: Given an observation O and an HMM λ, find another HMM λ' such that $P(O \mid \lambda') > P(O \mid \lambda)$.
Solution: We use the Baum-Welch algorithm, which is an EM algorithm (expectation-maximization).
The Baum-Welch algorithm uses a forward-backward procedure.
First, define $\gamma_t(j)$, which is the probability that the system λ is in state s_j at time t when producing the observation $X = (x_1, \dots, x_T)$:

$$\gamma_t(j) = \frac{P(q_t = j \mid X, \lambda)}{P(X \mid \lambda)} = \frac{\alpha_t(j) \cdot \beta_t(j)}{\sum\limits_i \alpha_t(i) \cdot \beta_t(i)} \tag{13}$$

To optimize a_{ij}, we need the probability $\xi_t(i, j)$ of being in state i at time t, transition from state i to j and be in state j at time $t + 1$.

$$\begin{aligned} P(q_t = 1, q_{t+1} = j \mid X, \lambda) &= \frac{P(q_t = 1, q_{t+1} = j, X \mid \lambda)}{P(X \mid \lambda)} \\ &= \frac{\alpha_t(i) \cdot a_{ij} \cdot b_j(x_{t+1}) \cdot \beta_{t+1}(j)}{P(X \mid \lambda)} \\ &= \xi_t(i, j) \end{aligned}$$

As a reminder (this follows from the rules of conditional probabilities):

$$P(A \mid B, C) = \frac{P(A, B \mid C)}{P(B \mid C)} \tag{14}$$

Define:

- $\sum\limits_t \gamma_t(i)$ expected # of times i is visited
- $\sum\limits_t \xi_t(i, j)$ expected # of transitions from i to j
- $\pi(i)$ expected frequency in i at time $(t = 1) = \gamma_1(i)$
- a_{ij} expected # transitions from i to j **div** expected # of transitions from i
- $b_i(v_k)$ expected # in i and observing k **div** expected # in state i

Now, we can define the new HMM $\lambda' = (S, \pi', A', B', V)$:

- $\pi'(i) = \gamma_1(i)$
- $a'_{ij} = \sum\limits_t \xi_t(i,j) \;/\; \sum\limits_t \gamma_t(i)$
- $b'_i(v_k) = \sum\limits_t \gamma_t(i) \cdot \delta(x_t, v_k) \;/\; \sum\limits_t \gamma_t(i)$ where $\delta(x,y) = (x \doteq y)$

Note that running the Viterbi algorithm leads to somewhat similar results. Training an HMM with Viterbi is faster, but when only little data is available, Baum-Welch performs better.

5.2 HMM state tying

When using Gaussian mixtures to model HMM output or transition probabilities, mixing more Gaussians doesn't necessarily lead to better results. This is due to an effect somewhat similar to overtraining.

- we use a simple three-state bakis model (similar to left-right model) for each phone
- the $b_i(x)$ are often Gaussian mixtures
- discrete HMMs are rarely used

5.2.1 Fully-continuous HMMs

- states that correspond to the same acoustic phenomenon share the same "acoustic model"
- for example, all */g/* phonemes may share the same model for the *g-b* HMM state
- the training data can be exploited better
- emission parameters can be estimated more robustly
- don't evaluate b for every state - save computation time!

See also figure 4.

hmm2.26

Figure 4: A fully-continuous HMM.

5.2.2 Semi-continuous HMMs

- only one codebook of Gaussians in the system
- every acoustic model has its own set of *mixture weights*

See also figure 5.

hmm2.27

Figure 5: A fully-continuous HMM.

5.2.3 Phonetically-tied semi-continuous HMMs

One codebook per phone that is shared across polyphones. For example, */g/* might have one codebook and */ae/* another.

5.3 HMM training

A typical HMM training session might look like this:

1. Initialization:
   - initialize all parameters randomly
   - or use pre-labeled data and compute initial parameters with e.g. **k-means**
2. Iterative optimization / training:
   - for all training utterances, run *Baum-Welch* and update the HMM accordingly
   - continue for a defined number of iterations or until there are no more improvements
3. Evaluation by recording an utterance and testing the HMM.

5.4 HMM parameter initialization

Use labeled data:

- automatic labeling
  - use an existing recognizer
  - probably suboptimal
- hand-made labels
  - manually assign HMM states to speech frames
  - probably time consuming
- use partial labels

6 Acoustic modeling

6.1 Discrete HMMs in continuous space

In ASR terminology, an HMM is *discrete* if the output space is partitioned into discrete, non-overlapping regions. The most common way to find such regions is to use k-means clustering. Then, the HMM states can emit discrete indices identifying one particular region.
A simple example of this is the regular partitioning of the F1-F2 formant space.

6.2 Source coding

- Scalar quantization:
  - for a scalar observation x, compute a quantization $y = Q(x)$
  - can be simple, such as rounding (e.g. $1.3 \to 1.0$ or $1.3948 \to 1.40$)
- Vector quantization:
  - divide large set of vectors into groups using e.g. k-means clustering
  - identify vectors by their group index
  - lossy data compression

6.3 Continuous HMMs

In ASR terminology, an HMM is *continuous* when the output space is continuous and so are the emission probabilities b_i. Often, Gaussians $b_i = \mathcal{N}(\mu_i, \Sigma_i)$ are used (μ_i is a k-dimensional vector, Σ_i is a $k \times k$ covariance matrix).
It is also possible to use a mixture of Gaussians:

$$b_i = \sum_{j=1}^{M} c_{ij}\mathcal{N}(\mu_{ij}, \Sigma_{ij}) \qquad \text{(or rather: } b_i = \sum_{j=1}^{M} c_{ij}\mathcal{N}(\mu_j, \Sigma_j) \quad ?)$$

where c_{ij} are the mixture weights.
If time is not an issue, we can use a continuous model. Otherwise, we will have to save computation time by altering our model.

6.3.1 Conversion to semi-continuous model

We "pull out" each Gaussian and collect them in a codebook. There will be a maximum of $M \cdot N$ Gaussians, where N is the number of states.

6.3.2 Conversion to shared semi-continuous model

We extend the mixture weights to include Gaussians that were initially assigned to other states. This means that many mixture weights which previously were 0 are now greater than 0. This results in even more parameters.

Problem: If we create one codebook for each emission probability, we end up with *a lot of* parameters. We may not have enough data to train our model.

Solution: Parameter tying. The most flexible way of parameter tying is to use an arbitrary number of Gaussian codebooks and an arbitrary number of mixture weight sets.

6.3.3 Conversion to tied semi-continuous model

Reduce the size of the codebook to a smaller size $L < M \cdot N$. Share Gaussians that belong to similar units (*tie units*). This "ties" the codebook elements (and states) together. The number of models to train is now manageable.

6.4 Parameter tying

There are two main approaches to parameter tying:

- **Knowledge driven:** Have an expert sit down and decide which parameters to tie.
- **Data driven:**
  - let n be the number of training vectors for a codebook, set the codebook size to $n \cdot f$ where f is an empirically found factor
  - run k-means with different values for k, choose the k with the best result
  - start with one codebook, train, once we have enough data, split
  - start with huge codebook, remove Gaussians with too few training counts, retrain
  - merge and split

The following parameters can be tied:

- sets of Gaussians
- within a mixture: have different Gaussians use the same covariance matrix
- transitions: different HMM states share the same transition probabilities

6.5 Lexicon

Problem: How do we connect our HMMs to words?

Solution: With a pronunciation dictionary.

In the simplest architecture, a word is represented as a sequence of phonemes and each HMM state represents one phoneme. In the lexicon, each word is bound to a phoneme sequence.

6.5.1 Pronunciation variants

One word can be pronounced differently due to:

- coarticulation effects
- dialects (e.g. *thing* vs. *thang*)
- various correct pronunciations (e.g. a = AE or a = EY)
- correct pronunciation differs from most commonly used ones (e.g. *February* vs. *Febyury*)

To solve this problem, we add variants to the pronunciation dictionary. When building an HMM for a word, we build multiple, alternative state sequences.

6.6 Context dependent acoustic modeling

Consider the pronunciation of *train* and *tell*. Common lexicon entries will be *T-R-EY-N* and *T-EH-L*, but the actual pronunciation often sounds more like *CH-R-EY-N* and *T-HH-EH-L*. The phoneme *T* sounds different depending on the phoneme following it.
At first, one might try to alter the lexicon entries, i.e. *CH-R-UW* instead of *T-R-UW*, but the *CH* in *true* sounds different from the one in *church*.
So, we introduce new acoustic units, such that lexicon entries might look like *T(R)-R-EY-N* and *T(vowel)-EH-L*. This means that we use context-dependent models of the phoneme *T*.

6.6.1 Crossword context modeling

It is not a good idea to assume that the left context of a word is silence. Because of this, we extend context modeling across word boundaries while building a sentence HMM.
Go to AM1 26/30 for more on this subject.

6.6.2 Position dependent modeling

The same phoneme (with the same context) is pronounced differently depending on its position in the word. As an example, consider the *D*-phoneme in *Idaho* and *my dad*. To solve this problem, we use position dependent modeling, where *wb* indicates a word boundary. In *Idaho*, this will become *D(AY, AE)*, whereas in *my dad*, it will become *D(wb)(AY, AE)*.

6.6.3 Parameter tying

With so many different states, even with lots of training data, the HMM cannot be trained enough. As a solution, we use parameter tying to combine multiple contexts into the same context class:

- Knowledge based:
  - let a linguist define classes C_i of phonemes (e.g. vowels, consonants, fricatives, etc.)
  - then, define generalized triphones for a monophone M: $M(C_l, C_r)$
- Data driven:
  - use some algorithm with an optimization criterion to decide which contexts should be tied
- Backoff procedure:
  - if we have enough training data for triphones, use triphones $P_m(P_l, P_r)$
  - otherwise, if we have enough training data for left or right context biphones ($P_m(P_l)$ or $P_m(P_r)$), use them
  - otherwise, as a fallback, use an indepent model P_m

6.7 Clustering

There are two different approaches to clustering:

- **bottom-up clustering** (agglomerative): start with one class for each phone, then combine "similar enough" classes until satisified
- **top-down clustering** (divisive): start with one class for all phones, divide a class if it seems like a "good idea", continue until satisfied

Both approaches result in a *clustering tree.*

Problem: How do we know whether it's a good idea to separate a class?

Solution: Use a *distance measure.*

6.7.1 Continuous parametric models

- $d(f, g) = \int \min(f(x), g(x))$
- Kullback-Leibler divergence: $d_{KL}(f, g) = \int f(x) \ln \frac{f(x)}{g(x)}$
- entropy distance: $d(f, g) = H(f + g) - \frac{1}{2}H(f) - \frac{1}{2}H(g)$

6.7.2 Discrete models

Semi-continuous and discrete HMMs are represented by *discrete* distributions.

- $H(f) = \sum\limits_i f[i] \log_2(\frac{1}{f[i]})$
- $d(f, g) = H(f + g) - \frac{1}{2}H(f) - \frac{1}{2}H(g)$
- obviously: $f = g \Rightarrow H(f) = H(g) = H(f + g) \Rightarrow d(f, g) = 0$

As an example, consider $f = \{\frac{1}{2}, \frac{1}{2}\}$, $g = \{\frac{3}{4}, \frac{1}{4}\}$. Then, $f + g = \{\frac{5}{8}, \frac{3}{8}\}$. It follows that $H(f) = 1$, $H(g) \approx 0.81$, $H(f + g) \approx 0.95$ and finally $d(f, g) \approx 0.05$.

Weighted discrete entropy distance

Consider three models M_1, M_f, M_{f+}, where M_1 is a model trained with many samples, M_f is a model trained with few samples and M_{f+} is a model that is trained with few samples, but more than M_f was trained with. Combining M_1 with M_f should have a smaller impact on the distance compared to combining M_1 with M_{f+}. Thus, we weigh the model entropy by the number of training samples:

$$d(f, g) = (n_f + n_g)H(f + g) - n_f H(f) - n_g H(g)$$

6.7.3 Kai-Fu Lee

1. train semicontinuous models for all three states of each triphone, e.g. triphone *A(AE,K)-b A(AE,K)-m A(AE,K)-e*.
2. initialize a context class for every triphone (a context class is defined by three distributions, e.g. T_{17}-*b*, T_{17}-*m*, T_{17}-*e*)
3. compute all distances between different context classes of same phone:
$$d(C_i, C_j) = E(C_i\text{-}b, C_j\text{-}b) + E(C_i\text{-}m, C_j\text{-}m) + E(C_i\text{-}e, C_j\text{-}e)$$
4. replace the two classes with the smallest class by their combination
5. try to improve distance by moving any element from any class into any other class

Note: This algorithm is completely data driven. Step 5 is expensive but important.

Kai-Fu Lee's algorithm produces *generalized triphones*. For example, *A(H,U)* and *A(B,P)* might be combined into *A37*, and *A(L,N)* and *A(M,M)* might be combined into *A38*.

6.7.4 Decision trees

After clustering, we might end up with two classes:

$$C_1 = \{P_1(P_2, P_3), P_1(P_4, P_5)\} \qquad C_2 = \{P_1(P_6, P_7), P_1(P_8, P_9)\}$$

Problem: If we want to recognize the word sequence P_3, P_1, P_7, do we use C_1 or C_2 to model $P_1(P_3, P_7)$?

Solution: Build a decision tree.

1. initialize one cluster containing all contexts
2. for all clusters and questions: compute distance of subclusters
3. perform the split that gets the largest separation

Figure 6: Growing the decision tree.

4. continue until satisfied

See figure 6 for an example.
Note: It doesn't matter which questions we ask, as long as our question set allows for a variable enough separation.

7 Language modeling

Remember the fundamental problem of speech recognition:

$$\operatorname*{argmax}_W P(X \mid W) \cdot P(W)$$

The purpose of the language model is to compute the probability $P(W)$ of a word sequence $W = (w_1, \ldots, w_n)$. For example, the LM should compute that "I owe you too" is more likely than "Eye O you two".
The difficulty of recognizing a word sequence is correlated to the *branching degree.* For example, the branching degree of *"I apologize for being late, I'm very —!"* is smaller than the one of *"Hello, my name is —."*.
In formal language theory, $P(W)$ is either 0 or 1. This deterministic approach is unsuitable for ASR because spoken language has complex grammatical rules and is often ungrammatical, anyway.
Thus, we employ statistical methods. The choice of the next word depends on the entire history. Since there are too many histories to test them all, we have to find equivalence classes $\mathcal{C}$ so that:

$$P(w \mid \text{history}) = P(w \mid \mathcal{C}(\text{history}))$$

A common choice for the equivalence classes are n-grams:

$$P'(w_k \mid w_1, \ldots, w_{k-1}) = P(w_k \mid w_{k-(n-1)}, \ldots, w_{k-1})$$

Usually, $P(w \mid \text{history})$ is estimated by counting relevant occurances:

$$P(w \mid \text{history}) = \frac{C(\text{history} \cdot w)}{C(\text{history})}$$

A language model is "good" if it has a low *perplexity.* The perplexity PP of a language model P on the test set $W = (w_1, \ldots, w_n)$ is:

$$PP = P(w_1, \ldots, w_n)^{-1/n}$$

The key problem of n-grams is the *data sparseness* problem: many n-grams will not occur in the training data, and many others will only occur very few times, resulting in inaccurate calculations. For example, in a several million word collection of English text, 50% of trigrams occur only once, and 80% of trigrams occur less than 5 times. As a start, we assign all strings a non-zero probability, in an effort to prevent ASR errors.

7.1 Smoothing

The idea of smoothing is to "free probability mass" from well-trained events and "redistribute" it to unseen events. This is somewhat similar to the idea of taxation.

7.1.1 "Add-one" smoothing

Add 1 to all bigrams:

$$\begin{aligned} P_{one}(w_i \mid w_{i-1}) &= \frac{C(w_{i-1}w_i)+1}{C(w_{i-1})+n_v} \\ &= (1-\lambda(w_{i-1}))\frac{C(w_{i-1}w_i)}{C(w_{i-1})} + \lambda(w_{i-1})\frac{1}{n_v} \end{aligned}$$

where $\lambda(w_{i-1}) = n_v \;/\; (n_v + C(w_{i-1}))$ and $n_v = |\{w : C(w) > 0\} \cup \{\text{UNK}\}|$. This means that we're mixing the estimated distribution with the uniform distribution. However, when n_v gets large, the estimation approximates the uniform distribution.

7.1.2 Backoff smoothing

Whenever possible, use higher-order models. Otherwise, for example with unseen events, backoff to lower-order models.

$$P_{bo}(w_i \mid w_{i-1}) = \begin{cases} \tilde{P}(w_i \mid w_{i-1}) & \text{if } C(w_{i-1}w_i) > 0 \\ \lambda(w_{i-1}) \cdot P_{bo}(w_i) & \text{otherwise} \end{cases}$$

Absolute discounting

Subtract a fixed D from each n-gram count:

$$P_{abs}(w_i \mid w_{i-1}) = \begin{cases} \frac{\max(C(w_{i-1}w_i)-D,0)}{C(w_{i-1})} & \text{if } C(w_{i-1}w_i) > 0 \\ \lambda(w_{i-1}) \cdot P_{abs}(w_i) & \text{otherwise} \end{cases}$$

Note: *This formula is probably incorrect. I think what we're trying to do is something like this:*

$$P_{abs}(w_i \mid w_{i-1}) = \begin{cases} \frac{C(w_{i-1}w_i)-D}{C(w_{i-1})} & \textit{if } C(w_{i-1}w_i) > D \\ \lambda(w_{i-1}) \cdot P_{abs}(w_i) & \textit{otherwise} \end{cases}$$

Or possibly even a weighted approach.

Good-Turing estimation

The idea is to reallocate the probability mass of n-grams that occur $r+1$ times in the training data to the n-grams that occur r times. In particular, reallocate the probability mass of n-grams that were seen once to the n-grams that were never seen.
For each count r, we compute an adjusted count r^*:

$$r^* = (r+1)\frac{n_{r+1}}{n_r}$$

where n_r is the number of n-grams seen exactly r times. Then, we compute the discount d_r:

$$d_r = \frac{r^*}{r}$$

Katz smoothing

Use k as a threshold to apply discounting. Use Good-Turing for discounting.

$$P_{katz}(w_i \mid w_{i-1}) = \begin{cases} \frac{C(w_{i-1}w_i)}{C(w_{i-1})} & \text{if } r > k \\ d_r \cdot \frac{C(w_{i-1}w_i)}{C(w_{i-1})} & \text{if } k \geq r > 0 \\ \alpha(w_{i-1}) \cdot P_{katz}(w_i) & \text{if } r = 0 \end{cases}$$

Kneser-Ney smoothing

As an example, let's suppose that "San Francisco" is common, but "Francisco" occurs only after "San". Then "Francisco" will get a high unigram probability and so absolute discounting will give a high probability to "Francisco" appearing after novel bigram histories (for example, "Los Francisco"). Since "Francisco" only ever occurs after "San", it is better to give it a low unigram probability. All in all, we use absolute discounting with a special backoff function. Define:

$$\begin{aligned} \#(\bullet\, w_i) &= |\{w_{i-1} : C(w_{i-1}w_i) > 0\}| \\ \#(\bullet\, \bullet) &= \sum_{w_i} \#(\bullet\, w_i) \end{aligned}$$

Then, define:

$$P_{KN}(w_i) = \frac{\#(\bullet\, w_i)}{\#(\bullet\, \bullet)}$$

7.1.3 Linear interpolation

Define:

$$P_I(w_i \mid w_{i-2}w_{i-1}) = \lambda \cdot \tilde{P}(w + i \mid w_{i-2}w_{i-1}) + (1 - \lambda) \cdot P_I(w_i \mid w_{i-1})$$

Key difference: in the case of non-zero counts, interpolated models still use information from lower-order models while backoff models do not.

7.2 n-gram classes

Another way to handle data sparsity is to group words into classes of similar semantic or grammatical behavior. For simplicity, let's assume that one word w_i can be assigned to only one class c_i. Then:

$$P(w_i \mid c_{i-(n-1)}, \ldots, c_{i-1}) = P(w_i \mid c_i) \cdot P(c_i | c_{i-(n-1)}, \ldots, c_{i-1})$$

n-gram classes have not improved recognition accuracy significantly.

7.3 Different kinds of language models

7.3.1 Cache language models

- **Idea:** Use a static and a dynamic component.
- **Static component:** $P_S(w_k \mid w_{k-(n-1)}, \ldots, w_{k-1})$, i.e. the usual trained language model.
- **Dynamic component:** Complete n-gram language model constructed from the text dictated so far, e.g.:

$$P_C(w_k \mid w_{k-(n-1)}, \ldots, w_{k-1}) = \frac{1}{2} \cdot f(w_k) + \frac{1}{4} \cdot f(w_k | w_{k-1}) + \frac{1}{4} \cdot f(w_k | w_{k-2}w_{k-1})$$

- **Total language model:** $P_T = \lambda_C \cdot P_C + (1 - \lambda_C) \cdot P_S$
- Compute P_C on last l words of cache, vary λ_C with cache size.

7.3.2 Trigger language models

- **Observation:** Often, when a content-carrying word occurs in a text, it is likely to occur again some time later.
- **Idea:** Use a standard interpolated n-gram model, but constantly update the unigram probabilities $P(w_k)$ for some words w_k.
- **Trigger:** For each word w define a trigger list $L(w)$ of words that are likely to occur some time later, e.g. $L(\text{money}) = \{\text{bank, savings, dollars}, \ldots\}$
- Then, for each word $v \in L(w)$, increase $P(v)$ by some value.

7.3.3 Multilevel language models

- **Idea:** Use language models LM_W for word sequences, LM_P for phrases and LM_S for sentences trained as regular n-gram grammars over their corresponding segments of speech.
- **Combination:** Let the total language model LM_T be a combination of the three models:

$$LM_T = \lambda \cdot LM_W + \lambda \cdot LM_P + \lambda \cdot LM_S$$

7.3.4 Interleaved language models

Sentences can often be split into two separate word sequences, one containing *content words* and the other containing *non-content words*:

sentence:	The	president	of the	software company said	that they will	introduce	...
non-content:	The		of the		that they will		...
content:		president		software company said		introduce	...

Based on this, we define:

$$P(w \mid \text{history}) = \begin{cases} P_C(w \mid C_1(\text{history})) & \text{if } w \text{ is a content word} \\ P_{NC}(w \mid C_2(\text{history})) & \text{if } w \text{ is a non-content word} \end{cases}$$

7.3.5 Morpheme-based language models

In heavily inflicted or agglutinating languages, the word stem is succeeded or preceded by gender-, tempus-, numerus- and case-identifying elements. The probabilities of full words cannot be estimated robustly. However, a robust estimation can be given for the word stem. So, we don't compute the language model on sequences of words but on sequences of morphemes:

$$P(w_1, \ldots) = \tilde{P}(w_{11}, w_{12}, \ldots, w_{1n_1}, \ldots)$$

7.3.6 Context-free grammar language models

Context-free grammars can be used instead of n-grams. The rules of the grammar can be written by an expert without the need for lots of training data. CFGs are powerful enough to represent large parts of natural languages and constrained enough to allow for efficient search space reduction. Furthermore, semantic analysis of speech is possible with CFG-derived finite state automata ($\rightarrow$ figure 7).

7.3.7 Tree-based language models

n-grams have a very limited context and training the parameters is almost impossible for large values of n. We can use a CART-based technique (classification and regression trees), where every tree node asks about k previous words ($k \approx 20$). Every leaf node is a unigram probability distribution on our vocabulary. This is somewhat similar to clustering acoustic context-dependent models ($\rightarrow$ figure 8).

lm2.9

Figure 7: Context-free grammar language models.

lm2.10

Figure 8: Tree-based language models.

7.3.8 HMMs for language modeling

Often, speech is carried out in phases, such as *greeting* $\rightarrow$ *smalltalk* $\rightarrow$ *good-bye*. Based on this, we can build an HMM, where every state emits language models or mixture weight distributions ($\rightarrow$ figure 9).

lm2.11

Figure 9: HMMs for language modeling.

7.4 Vocabulary selection

A small vocabulary eliminates potentially confusing candidates and improves the word error rate. A larger vocabulary has a lower out-of-vocabulary rate, but the word error rate increases. The goal is to balance the WER and OOV rates. We do this by using a corpus of text to determine appropriate vocabularies. For example, we can pick data from a specific domain and use the most frequent words.

7.5 n-gram pruning

The size of higher-order n-gram models if often too large for practical applications. We can employ n-gram pruning to reduce the model size. Experience shows that trigram models can be pruned by more than 25% without losing recognition accuracy.

7.6 Problems with spontaneous speech

- silence between words (*"hello world"* vs. *"hello   world"*)
- hesitations (*"ah"*, *"uhm"*, ...)

- filler words an phrases (*"I mean"*, *"you know"*, ...)
- false starts, aborts, etc. (*"let's meet sun- no saturday"*)
- non-verbal sounds (breathing, lip smacks, ...)

Possible solutions are:

- just ignore it (*duh!*)
- increase context width (e.g. use 4-grams instead of trigrams)
- skip spontaneous effects in the history

7.7 Unknown words

Note: *Here, "unknown word" refers to a word not seen in the training data, but occuring in the decoder vocabulary and dictionary - as opposed to not being known at all.*

In the acoustic model, we can handle words that have not been seen in the training set by defining their pronunciation(s) in the pronunciation lexicon. However, in most speech recognition tasks, we cannot train all words that might have to be recognized some time. Approaches to this problem include:

- rewrite all words in the training text that only occur one with UNK and treat every unknown word in the recognition run as UNK
- use a class-based language model and assign a class to every unknown word
- add new word into vocabulary and use cache language model to improve the parameters for subsequent recognitions

7.8 OOV words

OOV words are words that are not known at all. These words *must* lead to recognition errors. Ideally, every OOV word causes only one substitution, which would imply WER = OOV. Usually, there are follow-up errors: every OOV word causes between 1.5 and 2 errors on average.

7.9 Problems with different languages

- **Problem:** Highly inflecting languages pose more of a problem to language recognition. **Solution:** Use morpheme-based language models.
- **Problem:** Some languages, e.g. German allow arbitrary compounding of nouns. **Solution:** Decompose compound nouns.
- **Problem:** Some languages, e.g. Chinese have a different or no specified notion of words. **Solution:** Consider syllable-based language models.

7.10 Language model adaptation

Natural language is highly variable, depending on time (medieval German vs. current German), domain (fishing vs. politics), context (scientific paper vs. chatting with friends), etc.
Generally, we have a large background corpus $\mathcal{B}$ and a small adaption corpus $\mathcal{A}$ depending on the current task. The goal is to compute a robust language model. We can try to solve this problem by using language model adaptation (see also figure 10). There are three techniques of doing this:

- model interpolation
- constraint specification
- meta-information extraction

lm2.24

Figure 10: Language model adaptation framework.

7.10.1 Retrieval of adaptation data

We have to retrieve our adaption data froms somehwere:

- Generate text using a grammar.
- Accumulate $\mathcal{A}$ during the recognition process.
- Use a small corpus $\mathcal{A}$ as a seed for retrieval techniques (online databases and WWW).

7.10.2 Model interpolation

1. linear interpolation: $P(w_q \mid h_q) = (1-\lambda) \cdot P_A(w_q \mid h_q) + \lambda \cdot P_B(w_q \mid h_q)$
2. backoff:
$$P(w_q \mid h_q) = \begin{cases} P_A(w_q \mid h_q) & \text{if } C(h_q w_q) \geq T \\ \beta \cdot P_B(w_q \mid h_q) & \text{otherwise} \end{cases}$$
3. dynamic cache model: $P(w_q \mid h_q) = \sum_{\{c_q\}} P(w_q \mid c_q) \cdot P(c_q \mid h_q)$
4. maximum a-posteriori:
$$P(w_q \mid h_q) = \frac{\epsilon \cdot C_A(h_q w_q) + C_B(h_q w_q)}{\epsilon \cdot C_A(h_q) + C_B(h_q)}$$

7.10.3 Constraint specification

Idea: Extract features from corpus $\mathcal{A}$ that are used as constraints for the adapted SLM.

7.10.4 Meta-information extraction

Idea: Use corpus $\mathcal{A}$ to extract background information about the underlying subject matter. Improve upon the background model based on semantic classification.

8 Search

Isolated word recognition:

- for every applicable vocabulary word, compute it's score (DTW) and it's likelihood (Forward algorithm)
- report the word with the best score / likelihood

Continuous speech recognition:

- not only find state sequence in words
- but also find the word sequence

8.1 DTW optimization

- define start and end point
- path should be close to diagonal
- no two successive horizontal / vertical steps
- pruning: eliminate losers (with score $s < s_{best} - \Delta$)
- usually, we're only interested in the final score, so we can overwrite older values

Drawbacks of DTW include speaker dependency and inefficiency for large vocabularies.

8.2 Viterbi optimization

Use tree search (→ figure 11).

search1.17

Figure 11: Viterbi tree search optimization.

8.3 Advanced optimization techniques

8.3.1 Two-level DTW

1. for each remotely likely word begin time, compute DTW with open end within all words
2. for each word start and end times calculated in the previous step, combine words with DTW based on calculated scores

Obviously, this is extremely costly for large vocabularies and longer words.

8.3.2 Depth-first search

Depth-first vs. breadth-first corresponds roughly to *time-asynchronous* vs. *time-synchronous*.
A^* **search** (usually implemented with a stack decoder):

8.3.3 Viterbi beam search vs. A^* stack decoder

Beam search doesn't require a heuristic and it is appropriate for parallel implementation. However, it is not admissible, that is it might not find the best solution. Nowadays, beam search is usually preferred over A^* (though A^* is taken for search through n-best and lattice structures).

8.3.4 One stage dynamic programming

Use Viterbi within words. For the first state of each word, consider the best last state of all words as predecessor. In order to reconstruct the best word sequence, find the best predecessor word to the current word. Finally backtrace.
Note: *???*
All search techniques use two strategies for efficiency:

- **Sharing:** Keep intermediate results so that they can be reused by other paths without recomputation. For example, when computing the emission probabilities of *"can"* and *"cash"*, we can reuse the emission probabilities for the phonemes C and AE.
- **Pruning:** Disregard unpromising paths without wasting time exploring them further.

When using bigrams, the best predecessor depends only on the current word, this is possible by storing one backpointer for each active word end. When using trigrams, the best predecessor also depends on the successor of the current word. Then, things "get ugly" and we have to approximate a solution.
The transition into an initial state of a word Z is computed by maximizing (Viterbi / DTW) the scores / accumulated distances $C(W)$ of all word-final states in the previous time frame and adding the local acoustic score $am(Z)$: e.g. $C(X)+am(Z)$ vs. $C(Y)+am(Z)$. When using a grammar, we additionally have to add to the accumulated score a language model score $lm(Z)$, e.g. $C(X) + am(Z) + lm(X, Z)$ vs. $C(Y) + am(Z) + lm(Y, Z)$. Without a grammar, the best predecessor state is the same for all word-initial states, whereas with a grammar, the best predecessor state also depends on the word transition probability.

When using tree search with a language model, we have a problem. After making a word-to-word transition, we don't know which word we are entering, but this knowledge is required to properly compute the probability of the transition. The solution to this are **delayed bigrams**. We make every word's final state unique. That way, we know which word we processed when we are in the final state. At that point, we can incorporate the language model information into our calculation (hence, *delayed*) ($\rightarrow$ figure 12).

search2.15

Figure 12: Delayed bigrams.

8.3.5 Unigram lookahead

No bigram information can be included until word identity is known. Instead, we estimate the unigram information of the remainder subtree and include the bigram information as soon as possible (see also figure 13).

8.3.6 Multi-pass searches

Why use multiple passes in continuous speech recognition:

- we could use a good estimator for A^* search

search2.16

Figure 13: Unigram lookahead.

- in pruning we could use a good lookahead to prune away the "right" parts
- recover from errors resulting from delayed bigrams

Forward-backward search: first, run backward pass, then run forward pass using backward scores to do pruning. Problems:

- when using a search pass to compute information for pruning, it has to be a lot faster than the actual search pass
- it cannot produce better results than the actual search pass
- no runon recognition possible (start processing before sentence has finished)
- where do we get backward bigrams from?

Example for a multi-pass search: in the first pass, use a narrow beam and a fast but weak acoustic model to prune some paths. In the second pass, use a regular Viterbi search with a wider beam and a slower but more powerful acoustic model, considering that some areas have already been pruned in the first run.

8.3.7 Multiple hypothesises

Reasons:

- do postprocessing on all hypothesises using additional knowledge
- speech understanding
- manual recovery options for the users

When recognizing isolated words, simply report not only the best, but the n best results. In continuous speech recognition, we can either use multiple recognizers and report all their results, or let Viterbi not only remember the best predecessor, but the n best predecessors.
A problem with multiple hypothesises is that the results are often quite similar in respect to their content words, while the non-content words are more variable. This results in many "useless" hypothesis. But if we simply increase n, the system may become too slow. The solution to this is to use **word lattices** ($\rightarrow$ figure 14).

9 Text-to-speech synthesis

Typically, text-to-speech synthesis involves three steps:

1. **text analysis:** from strings of characters to words
2. **linguistic analysis:** from words to pronunciations and prosody
3. **waveform synthesis:** from pronunciations to waveforms

We use the *mean mel cepstral distortion* (**MCD**) as a quality measure (smaller is better).

search2.22

Figure 14: A word lattice.

9.1 Text analysis

- character encodings
- word segmentation
- numbers, symbols, non-standard words
  - anything not directly in the lexicon
  - OOV or novel forms
  - abbreviations, letter sequences, acronyms
- may require special rules
  - train rules for homographs
  - numbers, roman numerals

Text processing errors are the most common complaints in TTS. Examples:

- "My cat who *lives* dangerously has nine *lives*."
- "He stole $100 from the bank."
- "He stole *1996* cattle on 25 Nov. *1996*."
- "It's 13 *St.* Andrew *St.* near the bank."

We employ a "bunch of hacky rules":

- **splitter:** domain-independent tokenizer
- **token type classifier:** identify numbers and abbreviations, disambiguate homographs
- **token type expander**
- **language model**

9.2 Linguistic analysis

The lexicon should be as comprehensive as possible, but this is impossible. So, we have to pronounce OOV words, too.

9.2.1 Bootstrapping

1. select some frequently occuring words and build lexical entries from them
2. select an article of text
3. synthesize each unknown word, add correct words to list
4. repeat

9.3 Waveform synthesis

Concatinative synthesis:

- random word / phrase concat
- phone concat
- diphone concat ($|\text{phones}|^2$ transitions)
- sub-word unit selection
- cluster-based unit selection

10 Spoken dialog systems

A dialog is a verbal interaction of two or more agents over more than one utterance in order to establish a joint goal. A spoken dialog system is an autonomous, artificial system that engages in a dialog with a human and employs speech recognition and synthesis. Commonly, a complete interaction is referred to as a *session*, an *utterance* is one person's speech between two pauses, and a *turn* represents all utterances of one partner, until the other partner starts interacting. A *barge-in* happens when a turn is interrupted. There are two kinds of initiatives, the *system initiative*, e.g. "Please tell me your destination airport." (more rigid, less ASR errors) or the *mixed initiative*, e.g. "What flight are you interested in?" (less rigid, harder to recognize and understand).

sds.7

Figure 15: Components of a spoken dialog system.

A *discourse* is the entirety of information and structure of the ongoing dialog up to a certain point. Each new utterance must be interpreted in the light of the ongoing discourse and then included in it.

In order to represent a discourse, Montague grammars are commonly used (transform text into first order logic). Problem: "A man walks in the park. He whistles" $\rightarrow (\exists x : man(x) \wedge walksinpark(x)) \wedge (\exists x : whistles(x))$. What we need is *anaphora resolution.*

Don't forget *typed feature structures.* We can build *semantic grammars* with it.

Dialog strategies:

- **plan-based** system: the idea is that communication is the result of a plan (to do / achieve something)
- **grammar-based** system: there are adjacency pairs, such as *question* $\rightarrow$ *answer*, *proposal* $\rightarrow$ *acceptance*, etc.
- **finite-state grammars:** describe possible events with a finite state automata (simple to produce, but rigid)

- **rational agency:** formally describe rational behavior and then use formal proofs in order to deduce next steps
- **frame-based** systems: somewhat similar to web forms, additionally define *moves* (which may contain *conditions*) to ask for specific information
- **statistical systems:** learn optimal next system action from corpus of completed dialogs

The dialog system has to communicate with the ASR system. Returning only the best hypothesis is usually not sufficient. We may have to weigh hypothesises according to the dialog act expectations. Also, we should adapt the context to each turn (e.g. in a navigation system in Karlsruhe, *"Durlach"* will be more likely than *"Paris"*, which is different from most other contexts).

If our system is *multimodal*, we can also use gestures, etc.

11 Multilingual speech processing

We can't simply retrain on foreign data, because:

- different scripts, no vowelization, no writing system
- no word segmentation, rich morphology
- tonality, click sounds
- social factors such as trust, access, exposure and cultural background

For an overview of the system, see figure 16.

msp2.4

Figure 16: Overview of multilingual speech processing systems.

Let's try to build a language independent ASR system!

- language independent acoustic modeling
  - *International Phonetic Alphabet* easy to implement, easy to port to other languages
  - fully data-driven procedure
- universal language model: combine LMs of different languages to allow code switching

Multilingual acoustic modeling

1. - uniform multilingual speech database
   - monolingual recognizers for many languages
2. - combine monolingual acoustic models
   - share data across languages

Acoustic model combination

Sound production is *human*-specific, not *language*-specific. Thus, it is sufficient to represent sounds with the IPA.

1. build universal sound inventory based on IPA (485 sounds $\rightarrow$ 162 IPA sound-classes)
2. each sound class is represented by one phoneme which is trained through data sharing:
   - *m*, *n*, *s*, *l* occur in all languages
   - *a*, *e*, *i*, *o*, *u* and *p*, *b*, *t*, *d*, *k*, *g*, *f* occur in most languages
   - some data is not shared

Challenges

- Many ASR algorithms are language independent, but they require lots of training data. For many languages, not a lot of training data exists, so we need a different approach. For example, we might use intelligent learning systems.
- The contexts of sounds are language specific. How can we still use context dependent modeling?
  - multilingual decision context trees
  - specialize decision tree by adaptation

Web-derived pronunciations

Unsupervised training

Idea: decode untranscribed audio data, select data with high confidence, use selected data to train / adapt recognizer.

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