Speaker verification and diarization

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Speaker recognition

- Speaker identification – determine which of the set of enrolled speakers a test speaker matches
- Speaker verification – determine if a test speaker matches a *specific speaker*
- Speaker diarization – "who spoke when" segment and label a continuous recording by speaker

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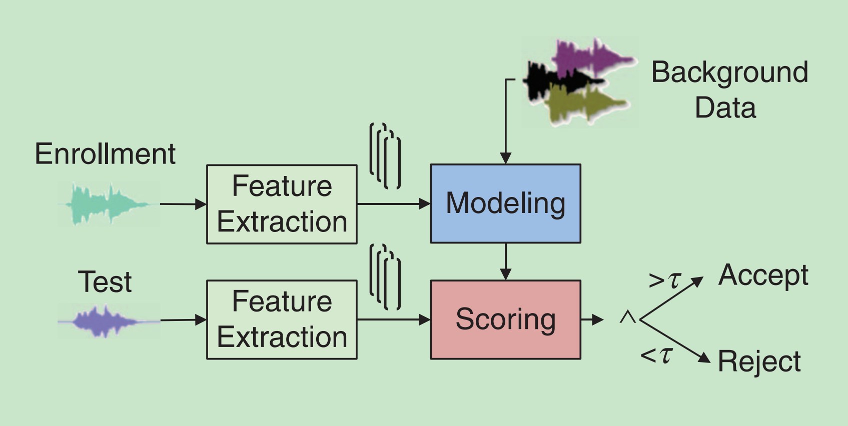
- Text dependent (vs text independent) – for speaker identification and verification, is the test speaker speaking a pre-defined utterance?
  - text-dependent – e.g. spoken password
  - text-independent – e.g. recognise a speaker from a law-enforcement recording
- Closed set (vs open set) – is there a fixed set of speakers?

Speaker verification

Overview of a speaker verification system



Source: Hansen and Hasan, 2015

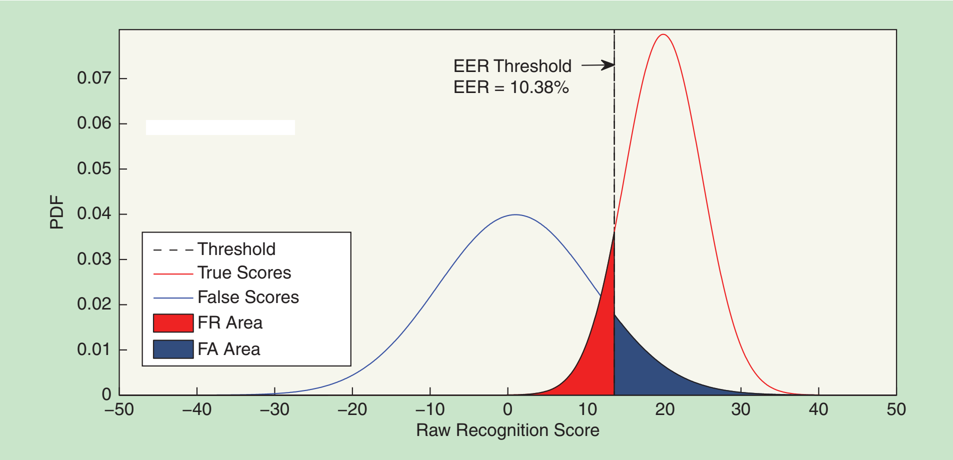
Evaluating speaker verification

- Two types of error
  - False acceptance – grant access to an imposter: **False Acceptance Rate (FAR)**
  - False reject – refuse access to a genuine speaker: **False Rejection Rate (FRR)**

$$\begin{aligned}\text{FAR} &= \text{False Alarm Probability} \\ &= \frac{\text{Number of imposters accepted}}{\text{Number of imposter attempts}} \\ \text{FRR} &= \text{Miss Probability} \\ &= \frac{\text{Number of legitimate speakers rejected}}{\text{Number of legitimate attempts}}\end{aligned}$$

- Control the levels of these errors by setting decision threshold
- Equal error rate – FAR and FRR values when they are equal
- DET (detection error tradeoff) curve – plots FRR (miss probability) against FAR (false alarm probability)

Speaker verification decision threshold



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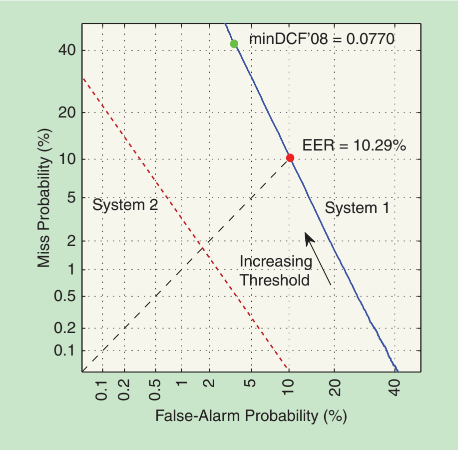
DET curve



Source: Hansen and Hasan, 2015

Detection cost function

- Detection cost function takes into account
  - Cost of miss (C_{miss}) and false alarm (C_{FA}) errors
  - Prior probability of target speaker – P_{target})
  - Miss probability at threshold τ – $P_{\text{miss}}(\tau)$
  - FA probability at threshold τ – $P_{\text{FA}}(\tau)$

$$DCF(\tau) = C_{\text{miss}} P_{\text{miss}}(\tau) P_{\text{target}} + C_{\text{FA}} P_{\text{FA}}(\tau)(1 - P_{\text{target}})$$

- Set $C_{\text{miss}} > C_{\text{FA}}$ if it is better to have false alarms than it is to miss the target speaker

Features for speaker verification

- Frame-level – typically use MFCCs or other features used in ASR
- Utterance/speaker-level – since we require to make decisions at the utterance level often aim to learn utterance level representations or embeddings
  - GMM supervectors
  - i-vectors
  - DNN embeddings
    - d-vectors
    - x-vectors

GMM-based speaker verification

- UBM (Universal Background Model) – train a GMM with many Gaussians (eg 2048) on the speech of the general population
  - NB: no sequence modelling (no HMM) - just a distribution over MFCCs
- Then adapt the UBM to each target speaker using MAP adaptation
- Directly use these GMMs to verify a target speaker using the log likelihood ratio (LLR), where X is the observed test utterance, θ_s is the target speaker model, and θ_0 is the UBM. :

$$LLR(X, s) = \log \frac{p(X|\theta_s)}{p(X|\theta_0)} = \log p(X|\theta_s) - \log p(X|\theta_0)$$

For a threshold τ

- If $LLR(X, s) \geq \tau$ then accept
- If $LLR(X, s) < \tau$ then reject

Recap: MAP adaptation

- Basic idea MAP adaptation balances the parameters estimated on the universal data with estimates from the target speaker
- Consider the mean of the mth Gaussian, $\boldsymbol{\mu}_m$
  - ML estimate of SI model:

$$\boldsymbol{\mu}_m = \frac{\sum_n \gamma_m(n)\mathbf{x}_n}{\sum_n \gamma_m(n)}$$

    where $\gamma_m(n)$ is the component occupation probability

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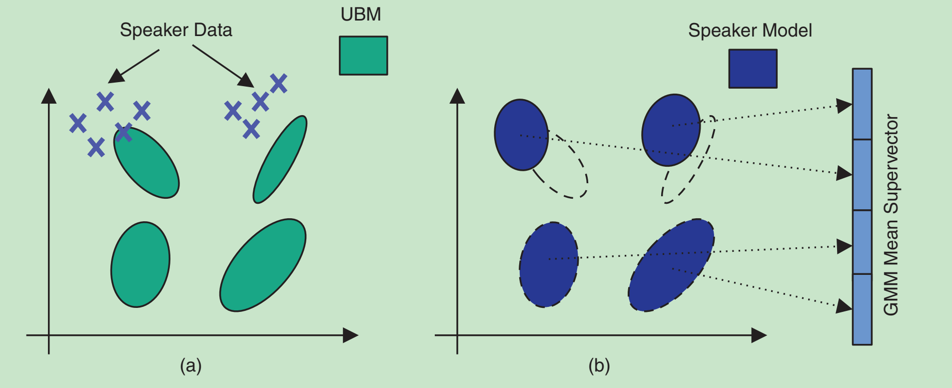
    where $\gamma_m(n)$ is the component occupation probability
  - **MAP estimate** for the adapted model:
    $$\hat{\boldsymbol{\mu}} = \frac{\alpha\boldsymbol{\mu}_0 + \sum_n \gamma(n)\mathbf{x}_n}{\alpha + \sum_n \gamma(n)}$$
    - α controls balances the SI estimate and the adaptation data (typically $0 \leq \alpha \leq 20$)
    - $\mathbf{x}_n$ is the adaptation vector at time n
    - $\gamma(n)$ the probability of this Gaussian at this time
  - As the amount of training data increases, MAP estimate converges to ML estimate

GMM UBM system



Source: Hansen and Hasan, 2015

i-Vectors

- Represent a speaker using the GMM (mean) parameters – concatenate the target speaker mean parameters to form a **GMM supervector** $\boldsymbol{m}_s$. Typical dimension of a UBM GMM is 2048, so with 39-dimension parameters, this can be a very high dimension vector ($\sim 80,000$ components)
- Represent the supervector for an utterance $\boldsymbol{X}_u$ as the combination of the UBM supervector and the utterance **i-vector** (Dehak et al, 2011):

$$\boldsymbol{m}_u = \boldsymbol{m}_0 + \boldsymbol{T}\boldsymbol{w}_u$$

  - $\boldsymbol{m}_u$ and $\boldsymbol{m}_0$ are D-dimension supervectors for the utterance u and the UBM
  - $\boldsymbol{w}_u$ is the **i-vector** ("identity vector") – a reduced dimension (d) representation for utterance u ($d \sim 400$)
  - $\boldsymbol{T}$ is a $D \times d$ matrix (sometimes called the "total variability matrix") which projects the supervector down to the i-vector representation
  - Estimate $\boldsymbol{T}$ for the development corpus using an EM algorithm, estimate the i-vector $\boldsymbol{w}_u$ for an utterance as the mean of the (Gaussian) posterior distribution of $\boldsymbol{w}_u$ given $\boldsymbol{X}_u$ and $\boldsymbol{T}$.

Speaker verification scoring using i-vectors

- Speaker verification involves computing a score $f(\boldsymbol{w}_{\text{target}}, \boldsymbol{w}_{\text{test}})$ between the target and test i-vectors
- Cosine score

$$f_{\cos}(\boldsymbol{w}_{\text{target}}, \boldsymbol{w}_{\text{test}}) = \frac{\boldsymbol{w}_{\text{target}} \cdot \boldsymbol{w}_{\text{test}}}{||\boldsymbol{w}_{\text{target}}|| \, ||\boldsymbol{w}_{\text{test}}||}$$

- Probabilistic linear discriminant analysis (PLDA) – probabilistic model that accounts for speaker variability and channel variability. Can be used to compute the log likelihood ratio, so

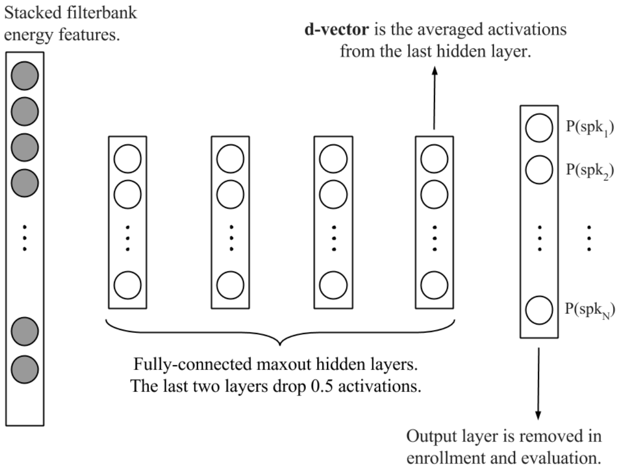
$$f_{\text{plda}}(\boldsymbol{w}_{\text{target}}, \boldsymbol{w}_{\text{test}}) = \log p(\boldsymbol{w}_{\text{target}}, \boldsymbol{w}_{\text{test}}|H_1) - \log \left[p(\boldsymbol{w}_{\text{target}}|H_0) p(\boldsymbol{w}_{\text{test}}|H_0) \right]$$

  where H_1 is the hypothesis that the test and target speakers are the same, H_0 is the hypothesis they are different
- PLDA is current-state of the art for scoring i-vectors

Neural network approaches

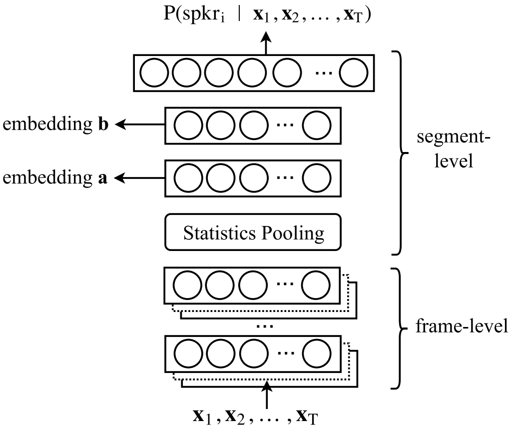
- Current state-of-the-art neural network approaches use NNs to extract embeddings, which are then scored by PLDA
- d-vectors (Variani et al, 2014)
  - Development – train a DNN to recognise speakers
  - Enrolment – extract speaker-specific features from last hidden layer
  - d-vector – average speaker-specific features across frames of an utterance (pooling)
- x-vectors (Snyder et al, 2018)
  - Similarly to d-vectors extract an utterance level feature as an embedding
  - Train TDNN with frame-level input and utterance-level output
  - Architecture includes a "stats pooling" layer which computes mean and SD across the utterance of the highest frame-level hidden layer

d-vector extraction



Source: Variani et al, 2014

x-vector extraction



Layer	Layer context	Total context	Input x output
frame1	$[t-2, t+2]$	5	120x512
frame2	$\{t-2, t, t+2\}$	9	1536x512
frame3	$\{t-3, t, t+3\}$	15	1536x512
frame4	$\{t\}$	15	512x512
frame5	$\{t\}$	15	512x1500
stats pooling	$[0, T)$	T	1500Tx3000
segment6	$\{0\}$	T	3000x512
segment7	$\{0\}$	T	512x512
softmax	$\{0\}$	T	512xN

Source: Snyder et al, 2018

Speaker diarization

Dealing with multiple speakers

- Speaker diarization is the "who spoken when" task: given a recording, divide it into segments, where each segment corresponds to speech of a single speaker
- Each recording contains multiple speakers – unlike what we have assumed so far for speech recognition and speaker verification
- Multiple speakers in a recording is realistic – many possible domains, e.g.:
  - Broadcast media
  - Telephone conversations
  - Call centres
  - Meeting recordings

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- Multiple speakers in a recording is realistic – many possible domains, e.g.:
  - Broadcast media
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  - Call centres
  - Meeting recordings
- A basic approach to diarization:
  Segment the recording into a sequence of short pieces, each assumed to be a single speaker. Then treat as a speaker verification task between all pairs of segmented utterances
  - Guaranteed to fail on segments with overlapping speakers!

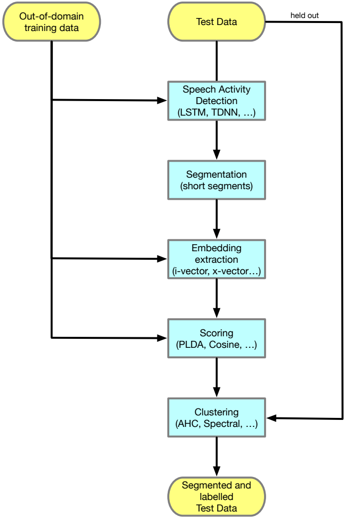
Measuring speaker diarization – Diarization error rate

- There are three main type of error to consider in speaker diarization:
  - **Missed speech** (E_{miss}): system labels a segment as non-speech, but segment is attributed to a speaker in the reference
  - **False-alarm speech** (E_{fa}): system attributes segment to a speaker, but segment is labelled as non-speech in the reference
  - **Speaker error** (E_{spkr}): system attributes segment to a speaker different to the reference attribution
- These errors are computed in a time-based way: each is expressed as a fraction of the scored time in the reference
- The diarization error rate (DER) is computed as a sum of these errors

$$DER = E_{\text{miss}} + E_{\text{fa}} + E_{\text{spkr}}$$

- Note that E_{miss} and E_{fa} arise from the speech activity detection

Framework for speaker diarization



Segment a recording, and attach a speaker label to each segment.

1. Split the recording into segments
2. Speech activity detection: identify whether each segment is speech or non-speech, discard non-speech
3. Represent the speech segments using some form of fixed length embedding: i-vector, x-vector, d-vector...
4. Compare all pairs of segments using a scoring metric such as PLDA
5. Cluster the segments using an algorithm such as agglomerative hierarchical clustering

Segmentation and Speech Activity Detection

- Speech activity detection (SAD) typically carried out using an LSTM or TDNN neural network trained on a large amount of diverse data
  - Binary output: speech vs. non-speech
  - Possibly with data augmentation – noise, reverb, etc.
- Following SAD, segment into short fixed-length segments (typically 2s)
  - Assumes each segment contains speech from a single speaker
  - In practice can use overlapping segments (overlap by 0.5s at start and end)
  - Relatively short segment duration for embedding computation

Speaker Embeddings and Clustering

- Compute a speaker representation for each segment
  - i-vector - typically 64-128 dimension
  - x-vector / d-vector - typically 128-256 dimension
  - can reduce the dimension by performing PCA on the set of embeddings for a recording
- Score all segment pairs – typically use PLDA
- Cluster segments – many possible clustering algorithms: Agglomerative hierarchical clustering can work well
  - Only need to compute pairwise segment scores once
  - Score for a cluster pair is obtained by averaging the pairwise scores between the segments in each cluster
- Determine the number of clusters
  - Clustering stopping criterion determines the number of clusters
  - Define a prior distribution on the number of speakers, and apply to clustering
  - Bayesian models with a prior on number of clusters – Variational Bayes (VB) HMM, Hierarchical Dirichlet Process (HDP) HMM, distance-dependent Chinese Restaurant Process (ddCRP), . . .

DIHARD

- R&D in speaker diarization has been very domain-dependent
  - 1990s – broadcast news (Hub4)
  - 2000s – multi-microphone meeting recordings (AMI, NIST RT)
  - 2010s – conversational telephone speech (CallHome)
- Had the effect of fragmenting the field
- Since 2018 the DIHARD Challenge (https://coml.lscp.ens.fr/dihard/) has focused on "speaker diarization for challenging recordings where there is an expectation that the current state-of-the-art will fare poorly" – diverse set of data sets used

Some hot topics in diarization

- Overlapping speech – most systems do not explicitly deal with this
- Speech activity detection is still a significant cause of error
- Development of end-to-end systems
- Bayesian approaches (learning the number of speakers/clusters from the data)
- Use of supervised learning

Summary

- i-vectors are the state-of-the-art speaker representation, used in
  - speaker recognition
  - speaker diarization
  - speaker adaptation in ASR
- NN speaker representations such as d-vectors and x-vectors are now competitive with i-vectors
- PLDA is the state-of-the-art scoring approach
- Current challenges include development of end-to-end NN approaches

Reading – speaker verification

- JHL Hansen and T Hasan (2015), "Speaker Recognition by Machines and Humans: A tutorial review", *IEEE Signal Processing Magazine*, 32(6):74–99, https://ieeexplore.ieee.org/document/7298570
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Reading – speaker diarization

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