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LIUM_SPKDIARIZATION: AN OPEN SOURCE TOOLKIT FOR DIARIZATION

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ABSTRACT

This paper presents an open-source diarization toolkit which is mostly dedicated to speaker and developed by the LIUM. This toolkit includes hierarchical agglomerative clustering methods using well-known measures such as BIC and CLR. Two applications for which the toolkit has been used are presented: one is for broadcast news using the ESTER 2 data and the other is for telephone conversations using the MEDIA corpus.

Index Terms— Speaker, Diarization, Toolkit

1. INTRODUCTION

In the NIST terminology, the process of diarization consists in annotating temporal regions of audio recordings with labels. The labels represent names of speakers, or their gender, the channel type (narrow bandwidth vs. wide bandwidth), the background environment (quite, noise, music...), or other characteristics present in the signal.

In the case of speaker diarization, the "who spoke when" annotation is performed without any prior information: neither the number of speakers, nor the identities of the speakers, nor samples of their voices are needed. The labels representing the speakers are automatically generated without matching the real identities of the speakers. A common approach for this task consists in detecting homogeneous audio segments, which each contain the voice of only one speaker. Then the generated segments are grouped into clusters, one speaker at a time.

The main recent methods are based on hierarchical clustering. The methods differ in choices of merging distance, of the stopping criterion and of the cluster model type (either mono-Gaussian models or Gaussian Mixture Models (GMMs)). The architecture of the system is partly guided by the nature of the documents it will be used on. According the results obtained in evaluation campaigns, systems can obtain very good results over broadcast news recordings by using BIC clustering followed by a CLR-like clustering [1, 2]. Systems based on HMM-BIC [3] or T-test distance [4] perform better than BIC clustering over meeting recordings. Whereas E-HMM shows better performance over telephone conversations [5].

Several toolkits distributed under open-source licenses are available on the web. One of the oldest is the CMU Segmentation toolkit which was released in 1997 [6] and was developed for the NIST broadcast news evaluation campaign. AudioSeg, under the GPL license, is a toolkit developed by IRISA during the ESTER 1 campaign in 2005. It includes an audio activity detector, BIC or KL2 segmenting and clustering tools and a Viterbi decoder. Mistral_Seg, under the GPL license, is dedicated to speaker diarization and relies

on the ALIZÉ speaker recognition library. It was the starting point for the development of LIUM_SpkDiarization.

The LIUM_SpkDiarization toolkit can be used in various ways, to target diverse applications.

In its default configuration, it is oriented towards speaker diarization of broadcast news. The resulting diarization is well suited for speech recognition: each segment is from a single speaker over a single channel with a length shorter than 20 seconds. This system is described in section 2.1. The LIUM transcription system based on Sphinx, used during the ESTER 2 campaign, was described in [2].

The toolkit provides elementary tools, such as segment and cluster generators, decoder and model trainers. Fitting those elementary tools together is an easy way of developing a specific diarization system. Section 2.2 shows how to build a diarization system for telephone conversations.

Technical information on how to use the toolkit is given in section 3. Moreover, it is easy to extend the toolkit by adding algorithms. Section 4 describes the main classes and algorithms available.

2. APPLICATIONS

2.1. Broadcast news diarization

The proposed diarization system was inspired by the system [1] which won the RT'04 fall evaluation and the ESTER 1 evaluation. It was developed during the ESTER 2 evaluation campaign for the transcription and diarization tasks, with the goal of minimizing both word error rate and speaker error rate.

Automatic transcription requires accurate segment boundaries. Although non-speech segments must be rejected in order to minimize insertion of words and to save computation time, segment boundaries have to be set within non-informative zones such as filler words. Indeed, having a word cut by a boundary disturbs the language model and increases the word error rate.

Speaker diarization needs to produce homogeneous speech segments; however, purity and coverage of the speaker clusters are the main objectives here. Errors such as having two distinct clusters (i.e., detected speakers) corresponding to the same real speaker, or conversely, merging segments of two real speakers into only one cluster, get heavier penalty in the NIST time-based evaluation metric than misplaced boundaries [7].

The system is composed of acoustic BIC segmentation followed with BIC hierarchical clustering. Viterbi decoding is performed to adjust the segment boundaries. Music and jingle regions are removed using GMMs, and long segments are cut to be shorter than 20 seconds. A hierarchical clustering using GMMs for speaker models is computed over the clusters generated by the Viterbi decoding.

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2.1.1. System description

The Sphinx 4 tools are used for the computation of features from the signal. For the first three steps described below, the features are composed of 13 MFCCs with coefficient C_0 as energy, and are not normalized (no CMS or warping). Different sets of features are used for further steps, similarly computed using the Sphinx tools.

Before segmenting the signal into homogeneous regions, a safety check is performed over the features. They are checked to ensure that there is no sequence of several identical features (usually resulting from a problem during the recording of the sound), for such sequences would disturb the segmentation process.

Segmentation based on BIC

A pass of distance-based segmentation detects the instantaneous change points corresponding to segment boundaries. The proposed algorithm is based on the one described in [6]. It detects the change points through a generalized likelihood ratio (GLR), computed using Gaussians with full covariance matrices. The Gaussians are estimated over a five-second window sliding along the whole signal. A change point, i.e. a segment boundary, is present in the middle of the window when the GLR reaches a local maximum.

A second pass over the signal fuses consecutive segments of the same speaker from the start to the end of the record. The measure employs ΔBIC , using full covariance Gaussians, as defined in equation 1 below.

The well known measures for segmentation task are the KL2 [6], the Gaussian divergence [1] and ΔBIC [8]. All of them are implemented in this toolkit.

BIC Clustering

The algorithm is based upon a hierarchical agglomerative clustering. The initial set of clusters is composed of one segment per cluster. Each cluster is modeled by a Gaussian with a full covariance matrix. ΔBIC measure is employed to select the candidate clusters to group as well as to stop the merging process. The two closest clusters i and j are merged at each iteration until $\Delta BIC_{i,j} > 0$.

ΔBIC is defined in equation 1. Let $|\Sigma_i|$, $|\Sigma_j|$ and $|\Sigma|$ be the determinants of gaussians associated to the clusters i , j and $i + j$. λ is a parameter to set up. The penalty factor P (eq. 2) depends on d , the dimension of the features, as well as on n_i and n_j , referring to the total length of cluster i and cluster j respectively.

$$\Delta BIC_{i,j} = \frac{n_i + n_j}{2} \log |\Sigma| - \frac{n_i}{2} \log |\Sigma_i| - \frac{n_j}{2} \log |\Sigma_j| - \lambda P \quad (1)$$

$$P = \frac{1}{2} \left(d + \frac{d(d+1)}{2} \right) + \log(n_i + n_j) \quad (2)$$

This penalty factor only takes the length of the two candidate clusters into account whereas the standard factor uses the length of the whole data as defined in [8]. Experiments in [1, 9] show that better results are obtained by basing P on the length of the two candidate clusters only. However, both penalty factors are implemented in the toolkit.

Segmentation based on Viterbi decoding

A Viterbi decoding is performed to generate a new segmentation. A cluster is modeled by a HMM with only one state, represented by a GMM with 8 components (diagonal covariance). The GMM is learned by EM-ML over the segments of the cluster. The log-penalty between two HMMs is fixed experimentally.

The segment boundaries produced by the Viterbi decoding are not perfect: for example, some of them fall within words. In order

to avoid this, the boundaries are adjusted by applying a set of rules defined experimentally. They are moved slightly in order to be located in low energy regions. Long segments are also cut recursively at their points of lowest energy in order to yield segments shorter than 20 seconds.

Speech detection

In order to remove music and jingle regions, a segmentation into speech / non-speech is obtained using a Viterbi decoding with 8 one-state HMMs. The eight models consist of 2 models of silence (wide and narrow band), 3 models of wide band speech (clean, over noise or over music), 1 model of narrow band speech, 1 model of jingles, and 1 model of music.

Each state is represented by a 64 diagonal GMM trained by EM-ML on ESTER 1 data. The features are 12 MFCCs completed by Δ coefficients (coefficient C_0 is removed).

Gender and bandwidth detection

Detection of gender and bandwidth is done using a GMM (with 128 diagonal components) for each of the 4 combinations of gender (male/female) and bandwidth (narrow/wide band). Each cluster is labeled according to the characteristics of the GMM which maximizes likelihood over the features of the cluster.

Each model is learned from about one hour of speech extracted from the ESTER training corpus. The features are composed of 12 MFCCs and Δ coefficients (C_0 is removed). The entire features of the recording are warped using a 3 second sliding window as proposed in [10], before the features of each cluster are normalized (centered and reduced).

The diarization resulting from this step fits the needs of automatic speech recognition: the segments are shorter than 20 seconds; they contain the voice of only one speaker; and bandwidth and gender are known for each segment.

The diarization system developed during the ESTER 2 evaluation campaign performs better than the one employed during the first edition of the ESTER campaign: it allowed a gain 0.8 point of word error rate when coupled with the same speech recognition system.

GMM-based speaker clustering

In the segmentation and clustering steps above, features were used unnormalized in order to preserve information on the background environment, which helps differentiating between speakers. At this point however, each cluster contains the voice of only one speaker, but several clusters can be related to the same speaker. The contribution of the background environment to the cluster models must be removed (through feature normalization), before a hierarchical agglomerative clustering is performed over the last diarization in order to obtain a one-to-one relationship between clusters and speakers.

Thanks to the greater length of the speaker clusters resulting from the BIC hierarchical clustering, more robust, complex speaker models can be used for this step. A Universal Background Model (UBM), resulting from the fusion of the four gender- and bandwidth-dependent GMMs used earlier, serves as a base. The means of the UBM are adapted for each cluster to obtain the model for its speaker.

At each iteration, the two clusters that maximize a given measure are merged. The default measures are the Cross Likelihood ratio (CLR) [11] and the Cross Entropy (CE/NCLR) [12, 13]. The GMM-KL2 measure described in [14], equivalent to the Gaussian divergence [1] applied on GMMs, is also available.

The clustering stops when the measure gets higher than a threshold set *a priori*.

2.1.2. Evaluation

The methods were trained and developed according to data from the ESTER/1 (2003-2005) and ESTER 2 (2007-2008) evaluation campaigns. The results of the 2008 campaign are reported in [15]. The data were recorded in French from 7 radio stations, and are divided into 3 corpora: the training corpus corresponding to more than 200 hours, the development corpus corresponding to 20 shows, and the evaluation corpus containing 26 shows.

During the evaluation, the LIUM obtained the best result: 10.80 % of Diarization Error Rate (DER) using the system described in section 2.1, completed by a post-filtering step. The post-filtering consists in removing segments longer than 4 seconds including silence, breath, and inspiration, as well as music fillers. Fillers are extracted from the first pass of the speech recognition process [2].

The result was 11.03 % of DER without post-filtering.

Table 1 shows the current result on the test corpus of ESTER 2: a DER of 10.01 % with no post-filtering. The gain of one point of DER results from improvements in the management of consecutive identical features and of aberrant likelihoods in the Viterbi decoder after the campaign.

Corpus	%Miss.	%F.A.	%Sub.	DER
africa 1	0.5 %	1.2 %	8.2 %	9.85 %
inter	1.7 %	1.8 %	7.9 %	11.42 %
rft	0.0 %	0.7 %	2.9 %	3.72 %
tvme	0.5 %	2.7 %	9.7 %	12.89 %
ESTER 2 Total	1.0 %	1.6 %	7.4 %	10.01 %

Table 1. DER over the ESTER 2 test corpus

The default set of thresholds was determined using the ESTER 2 development corpus. Thresholds should be adapted for other corpus. Without skills in the field of speaker diarization, this task can be difficult. LIUM.SpKdiarization includes an experimental tool that automatically performs the tuning by trying various sets of thresholds.

Table 2 shows the DERs obtained over the NIST RT'03 diarization corpus (3 shows of broadcast news in English) before and after tuning the thresholds. A gain of 1.3 point can be observed after tuning the thresholds.

Thresholds	%Miss.	%F.A.	%Sub.	DER
default	0.2 %	2.5 %	5.0 %	7.65 %
tuned	0.2 %	2.5 %	3.7%	6.36 %

Table 2. DER over the RT'03 test corpus

2.2. Telephone

For the ANR project Port-Media, the LIUM needs to segment and transcribe telephonic conversations drawn from the French corpus MEDIA [16]. This corpus contains telephonic dialogues which were recorded using a Wizard of Oz. Conversations focused on tourist information and hotel booking.

Reusing the toolkit developed for the broadcast news system allowed to quickly setup a telephonic diarization system.

2.2.1. System description

12 MFCCs are used, completed by the energy. The MFCCs are not normalized during the speech detection step whereas the cepstral

mean is removed during the speaker detection step.

Speech detection

This detection relies on a Viterbi decoding using 3 GMMs corresponding to speech, silence, and dial tone. Each GMM is composed of 16 Gaussians with diagonal covariance, and trained via the EM-ML algorithm over 20 recordings (1 hour of data) which were segmented automatically and controlled by a human.

Only the speech segments are kept for the next step.

Speaker detection

The speaker detection method is based on the E-HMM approach described in [5].

The conversation model is based on an HMM with 2 states. Each state characterizes a cluster, i.e. speaker, and the transitions model the changes between speakers.

A UBM with 16 diagonal components is trained over 4 hours of speech automatically extracted by the speech detector.

A first speaker model is trained on all the speech data. The diarization is modeled by a one-state HMM and the speech segments are labeled as speaker S_0 . A second speaker model is then trained using the three seconds of speech that maximize the likelihood ratio between model S_0 and the UBM. A corresponding state, labeled as S_1 , is added to the previous HMM.

The two speaker models are adapted according to the current diarization. Then, Viterbi decoding produces a new diarization. The adaptation and decoding steps are performed while the diarization differs between two successive runs.

2.2.2. Evaluation

The development corpus is composed of 9 dialogues (33 minutes) whereas the test corpus is composed of 8 dialogues (23 minutes). In the MEDIA corpus, each part of the conversation was recorded separately. In the evaluated corpus, both parts of the conversation were mixed, and provided as a single channel, 8 kHz signal.

The manual transcriptions of the dialogue are available. The boundaries of the segments were manually checked and corrected to be accurate enough for diarization evaluation.

Table 3 shows the DER obtained through development and evaluation. The system obtains 2.47 % of DER over the test corpus. This error rate is very low but the task is quite easy: there is a lot of silence among speaker utterances and there is very little speech overlap.

Corpus	%Miss.	%F.A.	%Sub.	DER
Dev	2.0 %	1.3 %	1.2 %	4.51 %
Test	1.6 %	0.6 %	0.3 %	2.47 %

Table 3. DER over the MEDIA development and evaluation corpus

3. USING THE LIUM.SPEDIARIZATION TOOLKIT

LIUM.SpKdiarization is written in Java, targeting version 1.6 of the language. It requires a Sun JRE. In order to compile or execute the toolkit, the following 3rd party packages are needed:

- *gnu-getopt* package to manage command lines with long options.
- *lapack* package to manage matrices (blas, f2util and lapack). Only the inversion method based on Cholesky decomposition is used, for inversion of full covariance matrices of Gaussians.
- *Sphinx4* and *jsapi* packages to compute MFCCs.

3.1. Quick Start

For convenience, those 3rd party packages are included in the precompiled version. This version also includes a UBM, gender models, speech/non-speech models, and MFCC configuration files. The execution of the jar file directly invokes the speaker diarization method dedicated to broadcast news recordings (as described in section 2.1).

3.2. Advanced Use

Most of the tools in the package take a diarization as input and generate another diarization as output. The exceptions are model trainers, which generate a model instead of a diarization.

The main tools allow performing segmentation, silence detection, hierarchical clustering, and Viterbi decoding using GMM models trained with EM or MAP. Another set of tools helps to handle the diarization, models or features files. The typical actions applied to diarizations are: filtering, merging, splitting, printing, or extracting.

Figure 1 shows a sample script for training a UBM. The first call of the java virtual machine initializes the model. The initial model contains one gaussian learned over the training data. Iteratively, the gaussians are split and trained (up to 5 iterations of EM algorithm) until the number of components is reached. The second call trains the GMM using the EM algorithm. After 1 to 20 iterations, the algorithm stops if the gain of likelihood between 2 iterations is less than a given threshold.

```
#!/bin/bash

show="ubm"

# Input segmentation file, %s will be substituted with $show
seg="./%s.seg"

# Where is the mfcc, %s will be substituted with the name of the segment
show
fMask="./mfcc/%s.mfcc"
# The MFCC vector description, here it corresponds to 12 MFCC + Energy
# spro4=the mfcc was computed by SPro4 tools
# 1:1:0:0:0:0:1 = present, 0 not present.
# order : static, E, delta, delta E, delta delta delta E
# 13: total size of a feature vector in the mfcc file
# 1:0:0:1 CMS by cluster
fDesc="spro4,1:1:0:0:0:0,13,1:0:0:1"

# The GMM used to initialize EM, %s will be substituted with $show
gmmInit="./%s.init.gmms"

# The output GMM, %s will be substituted with $show
gmm="./%s.gmms"

# Initialize the UBM, ie a GMM with 8 diagonal Gaussian components
java -Xmx1024m -cp ./LIUM_SpkDiarization.jar
fr.lium.spkDiarization.programs.MtrainInit --sInputMask=$seg
--fInputMask=$fMask --fInputDesc=$fDesc --kind=DIAG --nbComp=8
--emInitMethod=split_all --emCtrl=1,5,0.05 --tOutputMask=$gmmInit $show

# Train the UBM via EM
java -Xmx1024m -cp ./LIUM_SpkDiarization.jar
fr.lium.spkDiarization.programs.MtrainEM --sInputMask=$seg --fInputMask=
$fMask --emCtrl=1,20,0.01 --fInputDesc=$fDesc --tInputMask=$gmmInit
--tOutputMask=$gmm $show
```

Fig. 1. Example of script for LIUM_SpkDiarization

3.3. Experimental Use

Methods currently under development are stored in a Java package named "experimental". Classes of this package may be greatly modified or removed at any time.

In version 3.5 of LIUM_SpkDiarization, classes for named identification of speakers are being developed [17]. Classes provide new word transcription containers including named entity annotations, Semantic Classification Tree and methods for named identification

of speakers. However, this development affects other classes, so developers are incited to minimize the connections between experimental packages and stable packages.

4. PROGRAMMING WITH THE TOOLKIT

4.1. Containers

There are three main containers: one for show annotation, one for acoustic vectors, and one for models.

Cluster and segment containers

Segment and Cluster objects allow managing a diarization. A segment is an object defined by the name of the recording, the start time in the recording, and the duration. These three values identify a unique region of signal in a set of audio recordings.

A cluster is a container of segments, where segments are sorted first by name of recording, then by start time. A cluster should contain segments of the same nature: speakers, genders, background environments, etc.

Clusters are stored in an associative container, named ClusterSet, where the key, corresponding to the name of the cluster, is mapped to the cluster. Therefore, each cluster name should be unique in a ClusterSet. Figure 3 shows the standard way of iterating over clusters and segments. This class design helps data processing when the methods iterate on each segment of each cluster. This access fulfills the majority of the algorithms of hierarchical classification.

No constraint exists for the relationship of a given acoustic feature to a segment. An acoustic feature can belong to any one segment or several segments. No mechanism of checking is provided, and such checking remains the responsibility of the programmer.

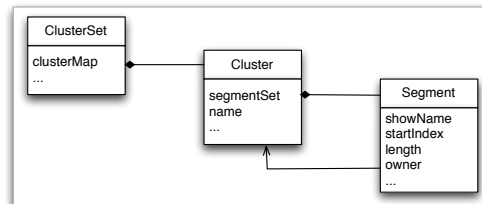


Fig. 2. Incomplete class diagram of ClusterSet, Cluster and Segment

Some situations require a temporal sequential access to the acoustic features, while for others random access is preferred, with possible access to cluster membership. Methods are provided to convert a ClusterSet into another container: a ClusterSet can be changed into a set of segments sorted first by record name, then by starting index; or into an array of segments where the index in the array corresponds to the index of an acoustic feature. This last container is available only if the ClusterSet refers to only one recording.

The toolkit uses its own diarization file format. However, diarizations can be saved to or loaded from files at the Sphinx CTL format that contains the list of utterances to decode.

Acoustic feature container

A FeatureSet stores the acoustic features, which are computed on the fly from the audio recording using Sphinx 4 classes or read from a file containing vectors of parameters. The supported file formats are Sphinx format, SPro4 format, and gzipped-text in which each line corresponds to a vector. The access to acoustic features of a FeatureSet is driven by the start index and end index stored in segments.

Common access to the acoustic features is illustrated in figure 3. There are two ways to access to a feature at a given index. The safe method takes two parameters: the name of the recording and the index of the acoustic feature to return. The second way activates the current recording in the FeatureSet before getting the acoustic features. The second way avoids testing for each feature access whether the current recording is the active one in the FeatureSet.

```
// Read a clusterSet file.
ClusterSet clusterSet = MainTools.readClusterSet(parameters);

// Read a FeatureSet file
FeatureSet featureSet = MainTools.readFeatureSet(parameters, clusterSet);

// Iterate over clusters
for(Cluster cluster: clusterSet.clusterSetValue()) {
    // Iterate over segments of the cluster
    for(Segment segment: cluster) {
        // Set the show name in featureSet.
        // If the current show name is different from the previous one,
        // the features of the current show name are read (or computed).
        featureSet.setCurrentShow(segment.getShowName());
        // Iterate over features of the segment
        int end = segment.getStart() + segment.getLength();
        for(int i = 0; i < end; i++) {
            // Get a feature, ie an array of float
            float[] feature = featureSet.getFeature(i);
            // alternative:
            // featureSet.getFeature(segment.getShowName(), i);
            for(int j = 0; j < feature.length; j++) {
                // ...
            }
        }
    }
}
}
```

Fig. 3. FeatureSet, ClusterSet, Cluster and Segment usage

Transformations can be applied before using the acoustic features. The first and second order derivatives as well as energy and its derivatives can be computed or deleted after reading the raw features. Feature distribution can be centered and/or reduced, given mean and variance vectors computed over a segment, over a cluster, over all the features of the recording, or over a sliding window. Indeed, a FeatureSet gets segments or clusters information from the ClusterSet given as a parameter when the FeatureSet instance is created. Feature warping is only suitable for sliding windows and can be combined with the previous normalization, before or after.

Section 2.1 shows that systems depend on various acoustic features. Segmentation and BIC clustering use only static and energy coefficients, speech/non-speech detection needs static and delta, and CLR clustering needed normalized static and delta, etc. Transformations reduce the number of feature sets stored on disk.

Models

Algorithms need to manage mono-Gaussian models with full or diagonal covariance or Gaussian Mixture Models (GMMs). Model classes follow the heritage graph shown in figure 4.

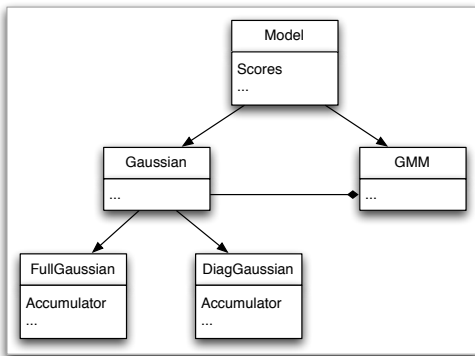


Fig. 4. Incomplete class diagram of models

The root class "Model" stores scores: the likelihood of the current feature, the sum and the mean of likelihoods accumulated by several invocations of the likelihood computation method. Accumulators should be initialized before use and reset by setting the accumulator to zero. In conjunction with the reset method, those storages permit to easily compute likelihood of a feature, *n* features, or segments.

Full and diagonal Gaussians implement an inner class to accumulate the statistics needed during an EM or MAP training. Those accumulators allow adding or removing weighted acoustic features to/from the accumulator before generating a new model. An illustration can be found in section 4.2.

4.2. Algorithms

Training

During the training of a model, the features indexed in the cluster are scanned and EM statistics are stored in the accumulators of the model. After the accumulation, we estimate the model by EM or MAP using the accumulators. The same algorithm is employed for training a mono-Gaussian model and for a GMM. Figure 5 illustrates an iteration of the EM algorithm.

```
// Initialize the statistic and score accumulators
gmm.initStatisticAccumulator();
gmm.initScoreAccumulator();

for(Segment segment: cluster) {
    featureSet.setCurrentShow(segment.getShowName());
    // Iterate over features of the segment
    for(int i = 0; i < segment.getLength(); i++) {
        float[] feature = featureSet.getFeature(segment.getStart()+i);
        // Get the likelihood of the feature (1)
        double lhGMM = gmm.getAndAccumulateLikelihood(feature);
        for (int j = 0; j < gmm.getNbOfComponents(); j++) {
            // Read the likelihood of component j computed in (1)
            double lhGaussian = gmm.getComponent(j).getLikelihood();
            // Add weighted feature in the accumulator of the GMM
            gmm.getComponent(j).addFeature(feature, lhGaussian / lhGMM);
        }
    }
}

// Compute the model according to the statistics
gmm.setModelFromAccumulator();
// Reset the statistic and score accumulators
gmm.resetStatisticAccumulator();
gmm.resetScoreAccumulator();
```

Fig. 5. Training a GMM from a cluster

Clustering

All clustering algorithms follow a bottom-up hierarchical approach (see figure 6). At initialization, the process trains the initial model of each cluster and computes the similarity measures between pairs of clusters. The process continues until the measure gets above a given threshold. According to the measures, at each iteration, the two most similar clusters are merged into a new cluster. During the merging, the model of the new cluster is trained and the similarities between this cluster and others are computed.

Decoding

A basic Viterbi decoder is available and the HMM models are based on the transformation of a set of GMMs. Each GMM is associated with an HMM. By default an HMM contains only one state but the minimum duration can be controlled by duplicating the state to form a string. HMM transition is fixed internally to 0, but the log penalties to switch between two HMMs needs to be set.

Decoding, as presented in figure 7, performs the forward pass in which statistics are accumulated. The best path across the states is defined by a diarization using the GMM name as cluster name. Aligned states are pushed as segments in the corresponding clusters.

```

// Get an instance of the BIC clustering class
BICHClustering clustering =
    new BICHClustering(clusterSet, featureSet, parameters);
// Set the threshold
double threshold = 0.0;
// Initialize the clustering: train models, compute measures between clusters
clustering.init();
// Get the highest measure of the two candidates for merging
double measure = clustering.getScoreOfCandidatesForMerging();

while (measure > threshold) {
    // Merge the two candidates, \ie
    // clustering.getFirstCandidate() and clustering.getSecondCandidate()
    clustering.mergeCandidates();
    // Get the highest measure of the two candidates for merging
    measure = clustering.getScoreOfCandidatesForMerging();
}
// Get the resulting diarization
return clustering.getClusterSet();

```

Fig. 6. Using a clustering algorithm

```

// Create a decoder
DecoderWithDuration decoder = new DecoderWithDuration();
// Setup the HMM states according the GMMs in modelSet and parameters
decoder.setupHMM(modelSet, parameters);

// Get the list of segments in the clusterSet
TreeSet<Segment> segmentList = clusterSet.getSegments();

// Iterate over the segments
for (Segment segment : segmentList) {
    // Accumulate decoder statistics, forward pass
    decoder.accumulate(featureSet, segment);
}
// Make the backward pass and return the diarization
return decoder.getClusters(clusterSet);

```

Fig. 7. Viterbi decoding

5. CONCLUSION

This paper presents a diarization toolkit mostly dedicated to speaker. Developed by the LIUM, this toolkit is published under the GPL license. When used for broadcast news diarization, it represents the state of the art in terms of performance. But its components can also be employed for other tasks with only minor work.

An interesting way to improve the toolkit will be implementing some missing methods. For example, methods such as [3, 4] are very useful to develop a system dedicated to meeting diarization.

Efforts should be done to bring the diarization toolkit closer to Sphinx 4. In particular, Sphinx 4 configuration management tools are very flexible and could be an efficient replacement for a number of scripts used with this toolkit. Moreover, the Viterbi decoder and access to acoustic features could adopt the Sphinx interface, thus helping developers to use both toolkits together.

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