End-to-end deep neural network based speaker recognition

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Problem Formulation

- Speech signal not only contains lexicon information, but also deliver various kinds of paralinguistic speech attribute information, such as speaker, language, gender, age, emotion, channel, voicing, psychological states, etc.

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- The core technique question behind it is utterance level supervised learning based on text independent or text dependent speech signal with flexible duration
- The traditional framework

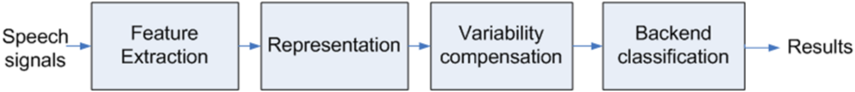

Figure: General framework

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Feature Extraction

- MFCC, PLP, SDC [1][1], PNCC[2][2], GFCC[3][3] , CQCC [4][4],etc.

[1] P. Torres-Carrasquillo et al. "Approaches to language identification using gaussian mixture models and shifted delta cepstral features". In: *Proc. of ICSLP*. 2002, pp. 89–92.

[2] C. Kim and R. M. Stern. "Power-Normalized Cepstral Coefficients PNCC for Robust Speech Recognition". In: *IEEE Transactions on Audio Speech and Language Processing* 24.7 (2016), pp. 1315–1329.

[3] Shao Yang and De Liang Wang. "Robust speaker identification using auditory features and computational auditory scene analysis". In: *Proc. of ICASSP*. 2008.

[4] Massimiliano Todisco, Hector Delgado, and Nicholas Evans. "Constant Q cepstral coefficients: A spoofing countermeasure for automatic speaker verification". In: *Computer Speech and Language* 45 (2017).

Feature Extraction

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- Bottleneck [5][1][6][2], Phoneme Posterior Probability [7][3][8][4], etc.

[1] Pavel Matejka et al. "Neural Network Bottleneck Features for Language Identification." In: *Proc. of Odyssey*. 2014.

[2] Achintya K Sarkar et al. "Combination of cepstral and phonetically discriminative features for speaker verification". In: *IEEE Signal Processing Letters* 21.9 (2014), pp. 1040–1044.

[3] Ming Li and Wenbo Liu. "Speaker verification and spoken language identification using a generalized i-vector framework with phonetic tokenizations and tandem features". In: *Proc. of Interspeech*. 2014.

[4] F. Richardson, D. Reynolds, and N. Dehak. "Deep Neural Network Approaches to Speaker and Language Recognition". In: *IEEE Signal Processing Letters* 22.10 (2015), pp. 1671–1675.

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[1] Florian Eyben, Martin Wöllmer, and Björn Schuller. "Opensmile: the munich versatile and fast open-source audio feature extractor". In: *Proc. of ACM Multimedia*. 2010, pp. 1459–1462.

[2] Hamid Behravan et al. "Introducing attribute features to foreign accent recognition". In: *Proc. of ICASSP*. IEEE. 2014, pp. 5332–5336.

[3] Ming Li et al. "Speaker verification based on the fusion of speech acoustics and inverted articulatory signals". In: *Computer speech & language* 36 (2016), pp. 196–211.

[4] Jinxi Guo et al. "Speaker Verification Using Short Utterances with DNN-Based Estimation of Subglottal Acoustic Features." In: *Proc. of INTERSPEECH*. 2016, pp. 2219–2222.

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- IMFCC[13][1], Modified Group Delay[14][2], etc.

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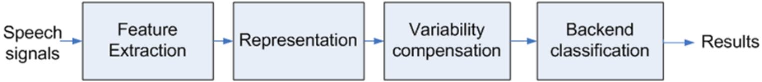
[1] Md Sahidullah, Tomi Kinnunen, and Cemal Hanilçi. "A comparison of features for synthetic speech detection". In: (2015).

[2] Zhizheng Wu, Eng Siong Chng, and Haizhou Li. "Detecting converted speech and natural speech for anti-spoofing attack in speaker recognition". In: *Proc. of Interspeech*. 2012.

Representation



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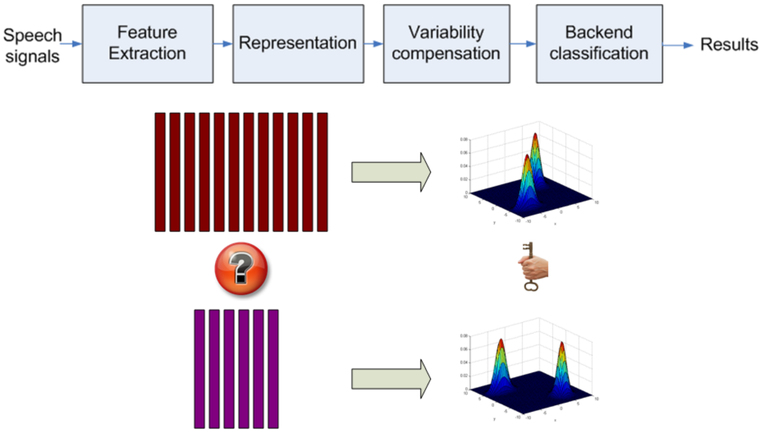

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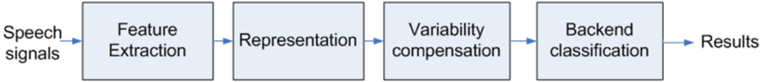

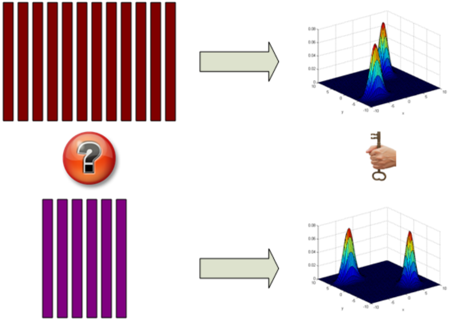

- time varying property $\Longrightarrow$ short time frame level features
- generative model for data description $\Longrightarrow$ features (supervectors) in model parameters' space for classification

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Generative model, adaptation, supervectors

- Gaussian Mixture Model (GMM) [15][3] serves as the generative model

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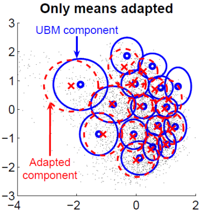

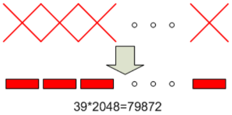

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    - Maximum Likelihood Linear Regression (MLLR) adaptation the linear regression matrix becomes GMM MLLR supervector [17][4]

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[4] Andreas Stolcke et al. "MLLR transforms as features in speaker recognition". In: *Ninth European Conference on Speech Communication and Technology*. 2005.

- The statistics vector for a set of features on UBM

Generative model, adaptation, supervectors

- The statistics vector for a set of features on UBM
  - 0^{th} order statistics vector N, centered normalized 1^{st} order statistics vector F

$$N_c = \sum_{t=1}^{L} P(c|\mathbf{y_t}, \lambda) \qquad (1)$$

$$\tilde{\mathbf{F}}_\mathbf{c} = \frac{\sum_{t=1}^{L} P(c|\mathbf{y_t}, \lambda)(\mathbf{y_t} - \boldsymbol{\mu}_\mathbf{c})}{\sum_{t=1}^{L} P(c|\mathbf{y_t}, \lambda)}. \qquad (2)$$

Cumulated by L frames

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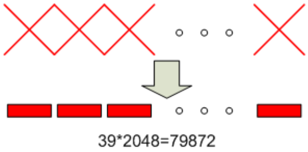

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- Mapping from a set of feature vectors to a fixed dimensional supervector

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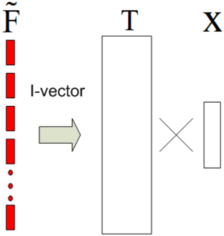
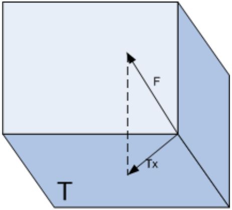
Factor analysis based dimension reduction

- Factor analysis on the concatenated centered normalized 1^{st} order statistics vector or GMM mean supervector





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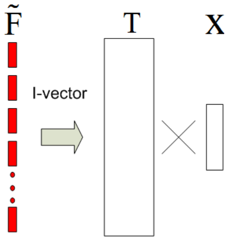
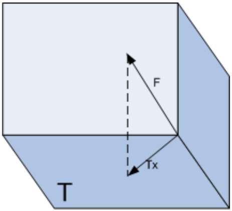
- Factor analysis on the concatenated centered normalized 1^{st} order statistics vector or GMM mean supervector
    - total variability i-vector [18][5]

$$\tilde{\mathbf{F}} = \mathbf{T}\mathbf{x} \qquad (3)$$

$\mathbf{T}$: factor loading matrix, $\mathbf{x}$: i-vector





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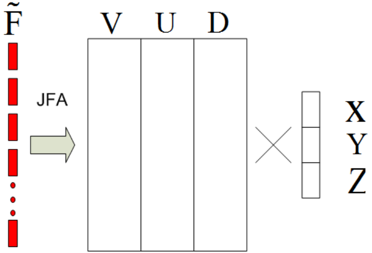
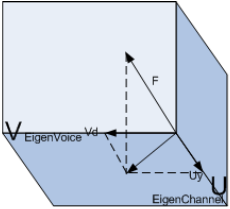
  - joint factor analysis (JFA) [19][6]

$$\tilde{\mathbf{F}} = \mathbf{V}\mathbf{x} + \mathbf{U}\mathbf{y} + \mathbf{D}\mathbf{z} \qquad (4)$$

V: Eigenvoices, **U**: Eigenchannels, **x**: speaker factor, **y**: channel factor, **D**: diagonal covariance matrix





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Variability Compensation

LDA, WCCN [20][7], NAP[16][8], NDA [21][9], LSDA [22][10], LFDA [23][11], etc.

[7] A.O. Hatch, S. Kajarekar, and A. Stolcke. "Within-class covariance normalization for SVM-based speaker recognition". In: *Proc. of INTERSPEECH*. Vol. 4. 2006, pp. 1471–1474.

[8] W.M Campbell et al. "SVM based speaker verification using a GMM supervector kernel and NAP variability compensation". In: *Proc. of ICASSP*. Vol. 1. 2006, pp. 97–100.

[9] Seyed Omid Sadjadi, Jason Pelecanos, and Weizhong Zhu. "Nearest neighbor discriminant analysis for robust speaker recognition". In: *Proc. of Interspeech*. 2014.

[10] Danwei Cai et al. "Locality sensitive discriminant analysis for speaker verification". In: *Proc. of APSIPA ASC*. 2016, pp. 1–5.

[11] Peng Shen et al. "Local fisher discriminant analysis for spoken language identification". In: *Proc. of ICASSP*. 2016, pp. 5825–5829.

Backend Classification

SVM [16][12], PLDA [24][13][25][14], NN [26][15][27][16], Joint Bayesian [28][17] , Cosine Similarity, etc.

[12]W.M Campbell et al. "SVM based speaker verification using a GMM supervector kernel and NAP variability compensation". In: *Proc. of ICASSP*. Vol. 1. 2006, pp. 97–100.

[13]S.J.D. Prince and J.H. Elder. "Probabilistic linear discriminant analysis for inferences about identity". In: *Proc. ICCV*. 2017.

[14]D. Garcia-Romero and C. Y Espy-Wilson. "Analysis of i-vector Length Normalization in Speaker Recognition Systems." In: *Proc. INTERSPEECH*. 2011, pp. 249–252.

[15]Kyu Jeong Han et al. "TRAP language identification system for RATS phase II evaluation". In: *Proc. of Interspeech*. 2013, pp. 1502–1506.

[16]Omid Ghahabi et al. "Deep Neural Networks for iVector Language Identification of Short Utterances in Cars". In: *Proc. of Interspeech*. 2016, pp. 367–371.

[17]Yiyan Wang, Haotian Xu, and Zhijian Ou. "Joint bayesian gaussian discriminant analysis for speaker verification". In: *Proc. of ICASSP*. IEEE. 2017, pp. 5390–5394.

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System Pipeline

Variable-length input → Local pattern extractor → Encoding layer → Feed-forward network → Loss function

- Speech signal is naturally with arbitrary duration. The input can be a hand-crafted short-term spectral feature (STFT spectrogram [29][18], Mel-filterbank energies [30][19], MFCC [31][20]), or even the raw waveform [32][21].

[18] Arsha Nagrani, Joon Son Chung, and Andrew Zisserman. "Voxceleb: a large-scale speaker identification dataset". In: *arXiv preprint arXiv:1706.08612* (2017). URL: http://www.robots.ox.ac.uk/~vgg/data/voxceleb/.

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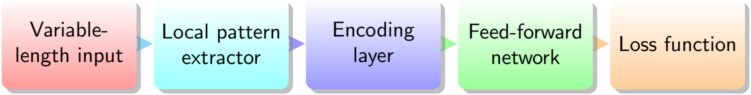

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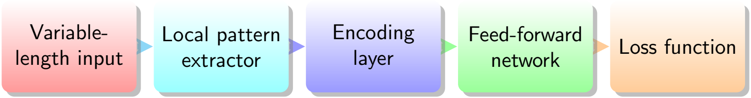

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- All the network components are jointly optimized with a global loss function. (Forward + Backward + Stochastic gradient descent)

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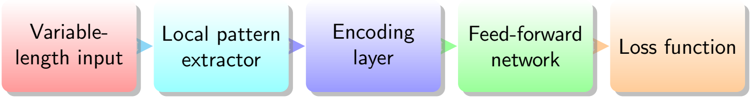

Task

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  Network outoput $\rightarrow$ Utterance-level posteriors
- Speaker Verification (Open-set)
  Utterance-level speaker embedding + Cosine / PLDA $\rightarrow$ Pairwise scores

Data preparation

Traditional workflow

- Off-the-shelf full-length utterance

Network workflow

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- The parameters are updated for each batch of data
- In the testing stage, arbitrary duration audio waveform → variable-length feature sequence → utterance-level fixed-dimensional embedding (e.g. x-vector).

DNN data preparation

D-vector [33][22][34][23][35][24]

- Raw feature sequences are broken into multiple small fixed-length data chunks at the frame level.

[22] Ehsan Variani et al. "Deep Neural Networks for Small Footprint Text-Dependent Speaker Verification". In: *Proc. of ICASSP*. 2014, pp. 4080–4084.

[23] Yuan Liu et al. "Deep feature for text-dependent speaker verification". In: *Speech Communication* 73 (2015), pp. 1–13.

[24] Lantian Li et al. "Deep speaker vectors for semi text-independent speaker verification". In: *arXiv preprint arXiv:1505.06427* (2015).

D-vector [33][22][34][23][35][24]

- Raw feature sequences are broken into multiple small fixed-length data chunks at the frame level.
- The input layer is fed with dozens of frames formed by stacking the currently processed frame and its several left–right context frames.

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[23] Yuan Liu et al. "Deep feature for text-dependent speaker verification". In: *Speech Communication* 73 (2015), pp. 1–13.

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D-vector [33][22][34][23][35][24]

- Raw feature sequences are broken into multiple small fixed-length data chunks at the frame level.
- The input layer is fed with dozens of frames formed by stacking the currently processed frame and its several left–right context frames.
- This data preparation procedure generates a large amount of temporary data chunks.

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X-vector [36][25]

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- In the testing stage, the full-length utterance-level feature sequence can be directly fed into the network.

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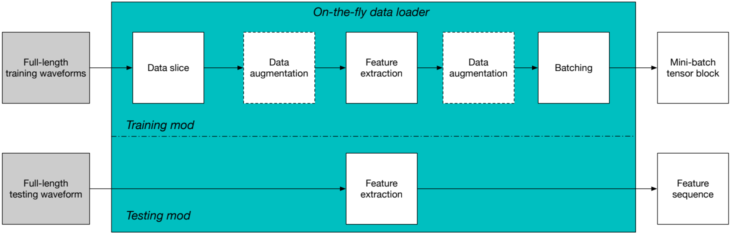

On-the-fly data loader [37][26]

- Offline augmentation requires us to generate all the necessary training samples into disk beforehand. On the contrary, a data loader here maintains an online processing work flow to generate training sample on the fly.

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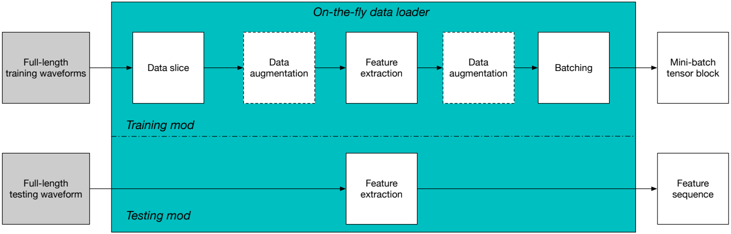

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- Offline augmentation requires us to generate all the necessary training samples into disk beforehand. On the contrary, a data loader here maintains an online processing work flow to generate training sample on the fly.
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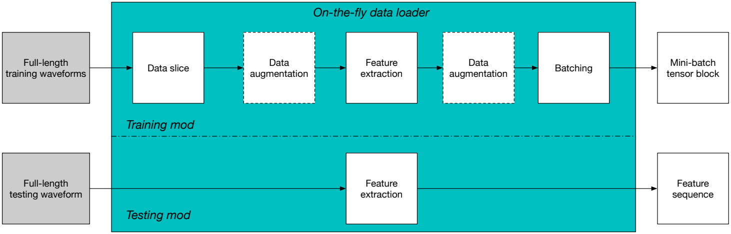

On-the-fly data loader [37][26]

- This design principle allows us to perform the batch-wise random perturbation, such as variable-length data slice and online data augmentation efficiently. All the operations are eagerly executed on the fly, and the training samples are generated in the memory just before feeding it into the DNNs.

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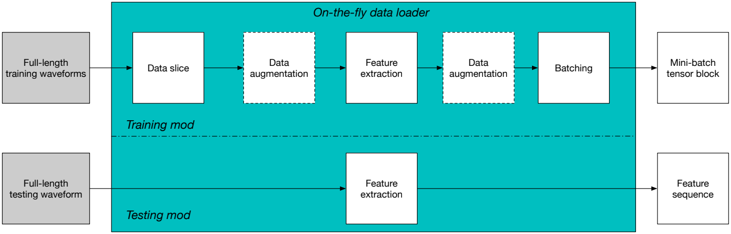

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- Since we maintain the dataflow from the raw waveform to the DNN output, it also promotes model inference and deployment ease. After the DNN has been trained, the data loader can simply tune into the "testing" mode by setting the batch size to one and removing the data slice, data augmentation and data batching modules.

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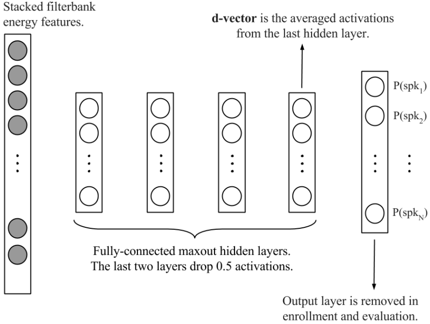
Network Structure

Feed-forward DNN(FF-DNN)



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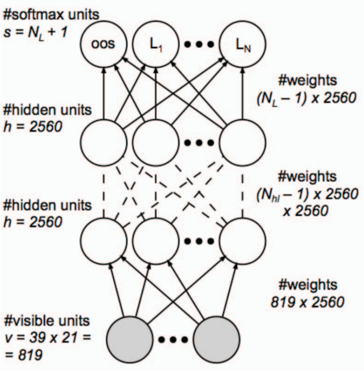

- FF-DNN for LID [38][28]

[28] I. Lopez-Moreno et al. "Automatic language identification using deep neural networks". In: *Proc. of ICASSP*. 2014, pp. 5337–5341.

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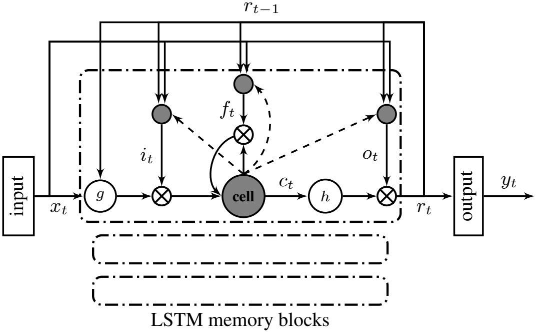
- Fram-level + Post average $\rightarrow$ Utterance-level

Network Structure

RNN/LSTM



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[29] J. Gonzalez-Dominguez et al. "Automatic language identification using long short-term memory recurrent neural networks". In: *Proc. INTERSPEECH*, pp. 2155–2159.

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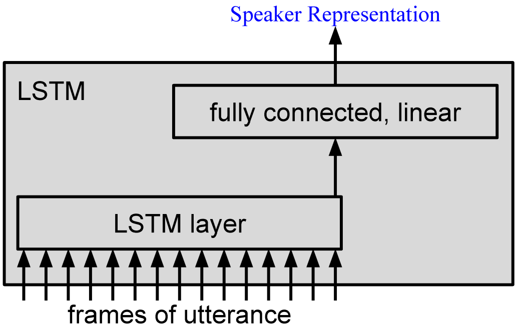

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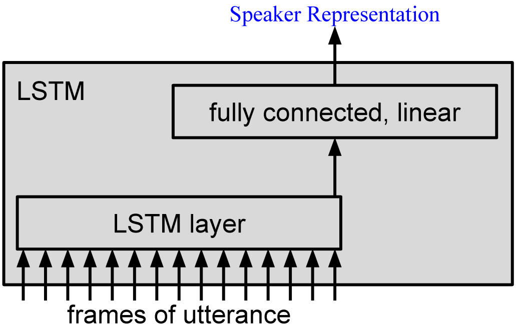

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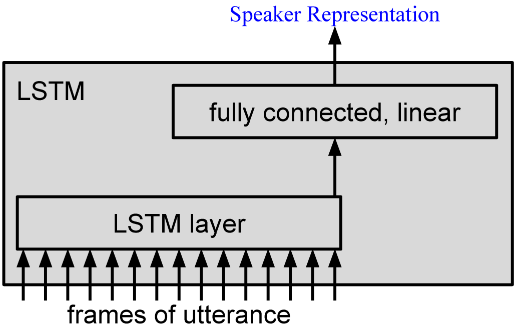

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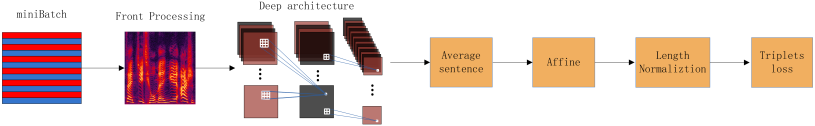

- CNN: Deep Speaker [30][30]

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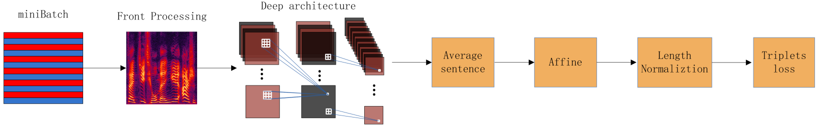

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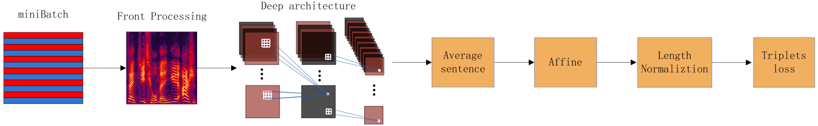

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[32] Weicheng Cai, Jinkun Chen, and Ming Li. "Exploring the Encoding Layer and Loss Function in End-to-End Speaker and Language Recognition System". In: *Proc. Speaker Odyssey*. 2018, pp. 74–81.

[33] Chunlei Zhang, Kazuhito Koishida, and John H. L. Hansen. "Text-independent Speaker Verification Based on Triplet Convolutional Neural Network Embedding". In: *IEEE/ACM Transactions on Audio Speech & Language Processing* 26.9 (2018), pp. 1633–1644.

Network Structure

TDNN

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

- x-vector [36][34]

[34] David Snyder et al. "X-vectors: Robust dnn embeddings for speaker recognition". In: *Proc. of ICASSP*. IEEE. 2018, pp. 5329–5333.

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Conventional approaches

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- Voting: An utterance-level results is derived by voting the frame-level DNN predictions.

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Data Augmentation

- Add noise, music, babble, reverberation [36][56]

[56] David Snyder et al. "X-vectors: Robust dnn embeddings for speaker recognition". In: *Proc. of ICASSP*. IEEE. 2018, pp. 5329–5333.

[57] Suwon Shon, Ahmed Ali, and James Glass. "Convolutional neural networks and language embeddings for end-to-end dialect recognition". In: *arXiv preprint arXiv:1803.04567* (2018).

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End-to-End Domain adaptation

- End-to-end adversarial training [67][65]

[65] G. Bhattacharya, J. Alam, and P. Kenny. "Adapting End-to-end Neural Speaker Verification to New Languages and Recording Conditions with Adversarial Training". In: *Proc. of ICASSP*. 2019, pp. 6041–6045.

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Table of Contents

Speech under Far Field and Complex Environment Settings

- Long range fading
- Room reverberation
  - Early reverberation (reflections within 50 to 100 ms): may improve the received speech quality
  - Late reverberation: smearing spectral-temporal structures, amplifying the low-frequency energy, and flattening the formant transitions, etc
- Complex environmental noises
  - fill in regions with low speech energy in the time-frequency plane and blur the spectral details

Previous Methods on Robust Modeling

- Signal level
  - Dereverberation: linear prediction inverse modulation transfer function filter [70][68], weighted prediction error (WPE) [71][69]

[68] B. J. Borgstrom and A. McCree. "The Linear Prediction Inverse Modulation Transfer Function (IP-IMTF) Filter for Spectral Enhancement, with Applications to Speaker Recognition". In: *Proc. ICASSP*. 2012, pp. 4065–4068.

[69] L. Mosner et al. "Dereverberation and Beamforming in Far-Field Speaker Recognition". In: *Proc. ICASSP*. 2018, pp. 5254–5258.

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[70] X. Zhao, Y. Wang, and D. Wang. "Robust Speaker Identification in Noisy and Reverberant Conditions". In: *IEEE/ACM Transactions on Audio, Speech, and Language Processing* 22.4 (2014), pp. 836–845.

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Previous Methods on Robust Modeling

- Model level
  - Reverberation matching with multi-condition training models within the UBM or i-vector based front-end systems [83][82],[84][83]
  - Multi-channel i-vector combination [85][84]
  - Multi-condition training of PLDA models [86][85]
- Score level
  - Score normalization [83][86]
  - Multi-channel score fusion [87][87],[88][88]

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Robust Modeling of End-to-End Methods

- DNN speaker embedding under far-field and noisy environment [89][89]

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Robust Modeling of End-to-End Methods

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  - For end-to-end methods with data augmentation, speech enhancement algorithms may cause mismatch between the training data (clean and augmented data) and the enhanced testing speech.

[89] M. K. Nandwana et al. "Robust Speaker Recognition from Distant Speech under Real Reverberant Environments Using Speaker Embeddings". In: *Proc. of INTERSPEECH*. 2018, pp. 1106–1110.

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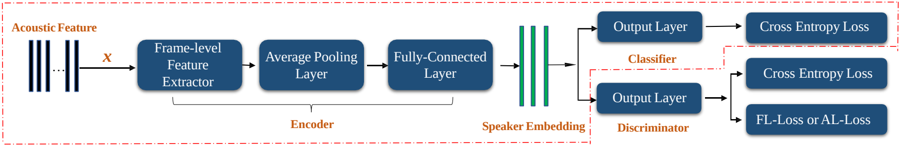
Robust Modeling of End-to-End Methods

- Multi-task adversarial network for noise-robust speaker embedding [69][91]
    - Encoding network for speaker embedding
    - Speaker classifier
    - Noise discriminator
    - Adversarial training by using fix-label loss or anti-label loss (take wrong label with cross entropy) of the noise discriminator
    - Outperform the other methods without adversarial training in noisy environments



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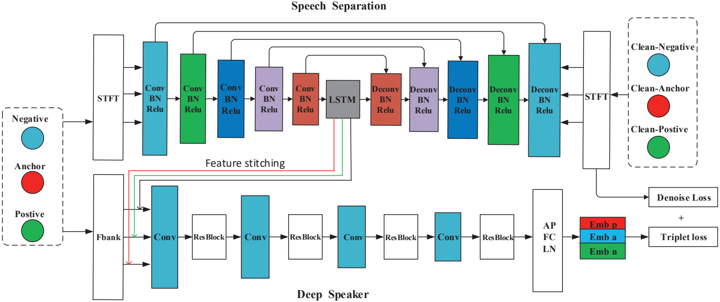
Robust Modeling of End-to-End Methods

- Joint training of denoising and speaker embedding network[91][92]
  - Denoising network
    - extract the target speech from noisy speech
    - extract bottleneck features
  - Speaker embedding network
    - Concatenate bottleneck features with fbank as inputs



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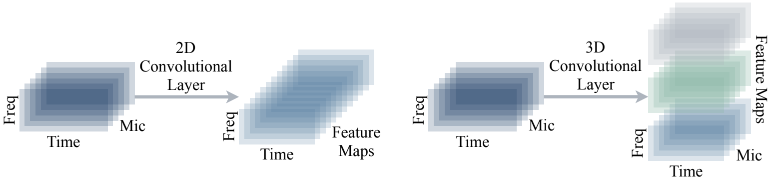
Robust Modeling of End-to-End Methods

- Multi-channel training framework for speaker recognition under reverberant and noisy environment [90][93]
  - 3D CNN structure as front-end convolutional network
  - Extract the time-, frequency-, and spatial-information
  - Significantly outperforms the i-vector system with front-end signal enhancement as well as the single-channel robust deep speaker embedding system



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Robust Modeling of End-to-End Methods

- Far-field text-dependent speaker verification [92][94]
  - Mixed training data with transfer learning
    - Utilize the content and speaker diversity of text-independent data
    - Train model with text-independent data and perform transfer learning with text-dependent data
  - Enrollment data augmentation
    - Enrollment and testing speech can be collected in different environmental settings (e.g. Cell phone enroll, Smart speakers test)
  - Corpus: AISHELL-2019B-eval dataset [95]
    - Open source wake-up words speech database

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HI-MIA Database Paper

Xiaoyi Qin, Hui Bu, Ming Li, "HI-MIA : A Far-field Text-dependent Speaker Verification Database and the Baselines", submitted to ICASSP 2020.

Ongoing Research Topics in DKU-SMIIP Lab

Robust Speaker Verification (far-field, multi-channel, noisy, etc.)
Robust Speaker Diarization (single channel, multi-channel, far-field, noisy, etc.)
Speech Separation/Enhancement (speech/music, supervised voice-filter, etc.)
Multi-Speaker TTS, Voice Conversion
Replay Detection Anti-Spoofing Database
Paralinguistic Speech Attribute Recognition
Acoustic Scene Analysis/Environmental Sound Classification

Summary

1. Problem Formulation

2. Traditional Framework
   - Feature Extraction
   - Representation
   - Variability Compensation
   - Backend Classification

3. End-to-End Deep Neural Network based Framework
   - System Pipeline
   - Data Preparation
   - Network Structure
   - Encoding Mechanism
   - Loss Function
   - Data Augmentation
   - Domain Adaptation

4. Robust Modeling of End-to-End methods
   - Speech under Far Field and Complex Environment Settings
   - Previous Methods on Robust Modeling
   - Robust Modeling of End-to-End Methods

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