End-to-End DNN based speaker recognition inspired by i-vector and PLDA

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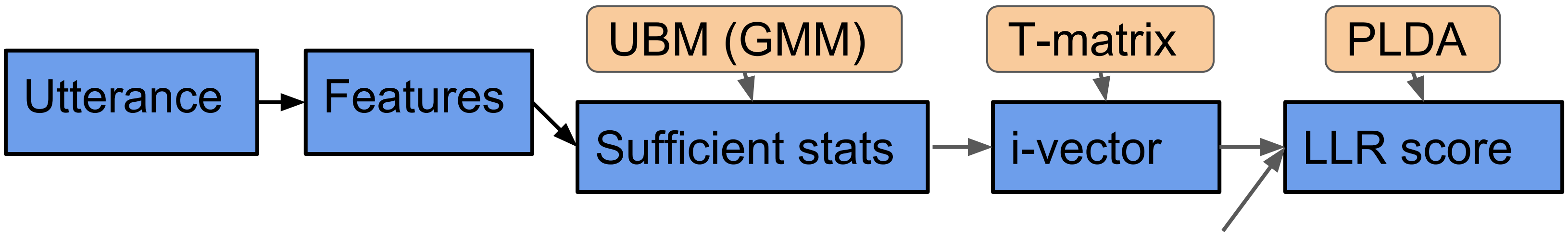
Background

- i-vectors and PLDA have been the state-of the art for many years



- Parts of i-vector+PLDA systems have been replaced by NNs
  - MFCCs → bottleneck features[1], UBM → DNN acoustic models[2]
    PLDA → DBNs[3], UBM and T-matrix → single NN[4,5]
- End-to-end systems replace the whole system by one NN
  - Successful for short utterances[6,7] but less successful for long[7]
  - Usually trained on short utterances
  - Training on long utterances may overfit and requires large memory

[1] Lozano-Diez et al. Odyssey 2016; [2] Lei et al. ICASSP 2014; [3] Ghahabi et al. ICASSP 2014; [4] Variani et al. ICASSP 2014; [5] Snyder et al. SLT 2016; [6] Heighold et al. 2016; [7] Snyder et al. SLT 2016

This work

- Develop an end-to-end system that is initialized to mimic an i-vector + PLDA system, then refined with end-to-end training

  1. First develop the individual blocks:
     - Feature to stats (**f2s**) NN: Collection of sufficient statistics
     - Stats to ivector (**i2s**) NN: i-vector calculation
     - **DPLDA**: Scoring
  2. Plug the blocks together and optimize them jointly for the speaker verification task, i.e., with end-to-end training on long and short utterances

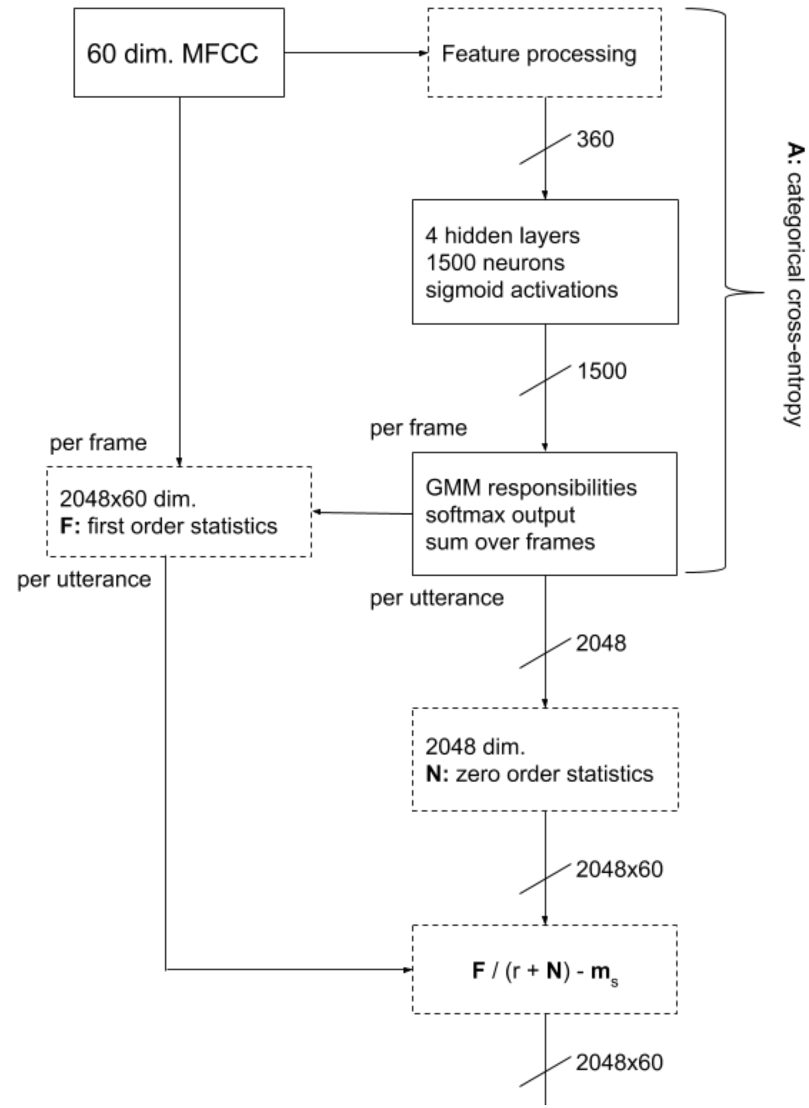
- To find good architecture and initialization for end-to-end training
- Avoid overfitting by regularizing towards initial model
- Good performance on long and short multi language conditions

Data and baselines

- Training data based on PRISM dataset
  - SRE 04-10, Fisher, Switchboard
  - UBM, iXtractor uses all training data
  - PLDA and DPLDA use only telephone data but use also short cuts created from non-English and non-native-English data
- Testing on language PRISM condition and SRE16 single enroll
  - We also cut PRISM lang into short segments to mimic SRE16
- All of our features are standard MFCCs+Δ+$\Delta\Delta$ (60 dimensions)
- Baselines are generative and discriminative PLDA based on 600-dimensional i-vectors extracted with 2048-component diagonal-covariance UBM

Features to sufficient statistics (**f2s**)

- Train NN to predict UBM responsibilities
- Input: processed and expanded features
  - Dimensionality: 360
  - Context: 30 Frames
- Output: GMM responsibilities
- Training objective: Categorical cross-entropy (soft targets)
- Given features and responsibilities, calculate sufficient statistics



f2s Architecture

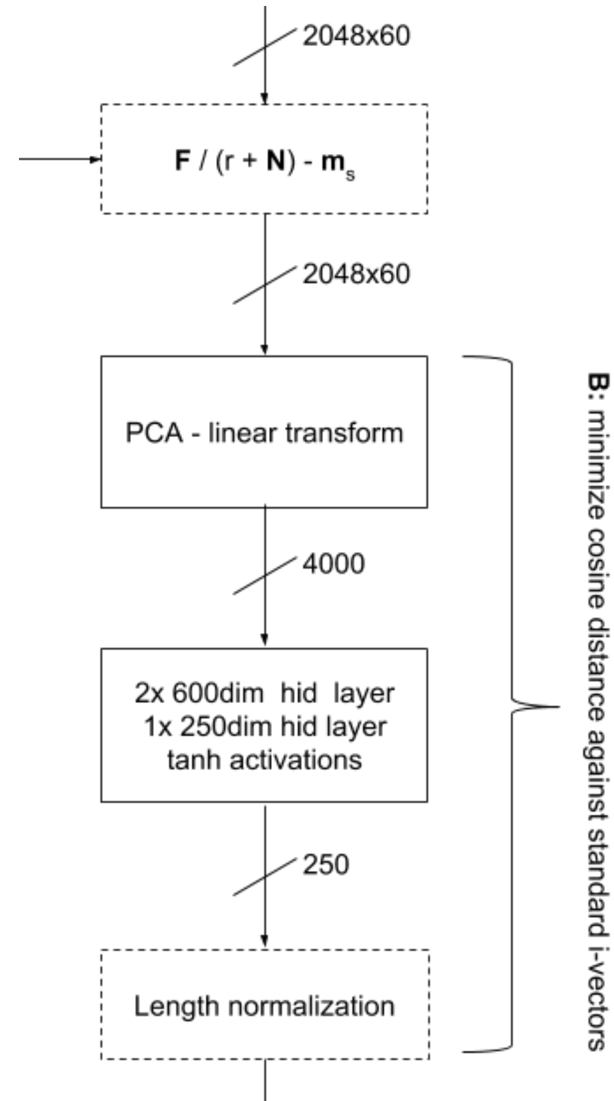
Developments on SRE10, core-core condition 5

Model	EER [%]	mindcf0.01	mindcf0.005
Baseline (GMM)	2.37	0.245	0.294
NN (60_1500_1500_2048)	2.27	0.242	0.293
NN (360_1500_1500_2048)	2.20	0.231	0.278
NN (360_1500_1500_1500_1500_2048)	**2.17**	**0.228**	**0.279**

- Larger context results in better predictions of the responsibilities
    - Probably because of increased robustness to unseen test conditions

Sufficient statistics to i-vectors (s2i)

- Model for initializing **e2e** system is trained on the output from **f2s**
- Input preprocessing
  a. Calculate relevance MAP adapted supervector (r=16)
  b. Reduce it by PCA from 2048 x 60 = 122880 to 4000 dim.
- 2 hidden layers with 600 units, tanh activation functions followed by affine transform and “length-norm”
- Output: LDA reduced and length-normalized i-vectors
- Training objective: Cosine distance



S2i architecture

	EER [%]	mdcf0.01	mdcf0.005
BASELINE	2.41	0.246	0.295

Developments on SRE10, core-core condition 5

- PCA dimension: 4000 (higher was not better), NN (4000_600_600_600)
- Mean square error objective

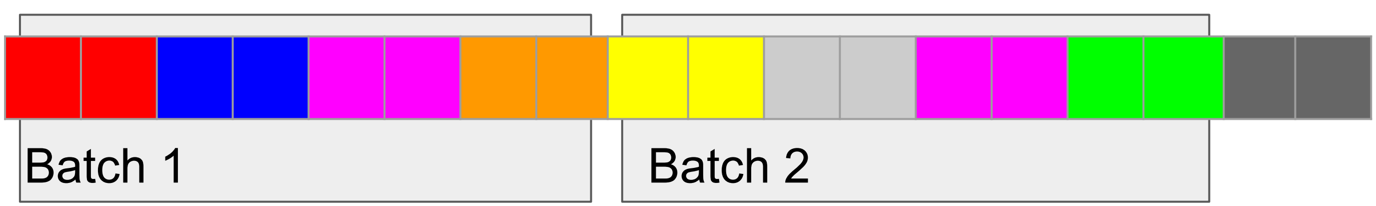
Target ivectors	NN Output	EER [%]	mdcf0.01	mdcf0.005
Length norm	Affine	2.86	0.290	0.346
WC norm. + Length norm	Affine	2.76	0.276	0.321
WC norm. + Length norm	Affine + Length norm.	2.59	0.270	0.313

- Cosine distance objective

WC norm. + Length norm	Linear -> Length norm	2.56	0.269	0.311
+ LDA	Affine + Length norm.	2.55	0.257	0.310
+ L1 reg	Affine + Length norm.	**2.43**	**0.256**	**0.306**

I-vectors to scores (DPLDA)

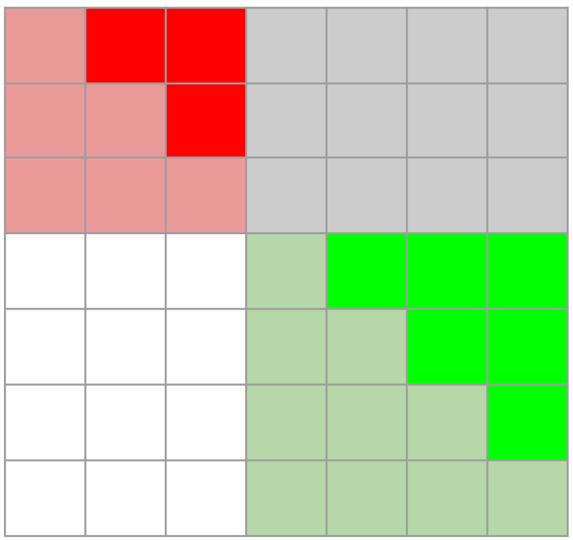
- The DPLDA baseline is trained iteratively using full batches (L-BFGS)
- For joint training with other blocks we use minibatches
- Minibatch approach in experiments:
  a. Group all utterances into pairs of the same speakers
  b. Shuffle the pairs
  c. Select *N* pairs (without replacement) to form a minibatch



- Training objective: Binary cross-entropy for all trials in the batch

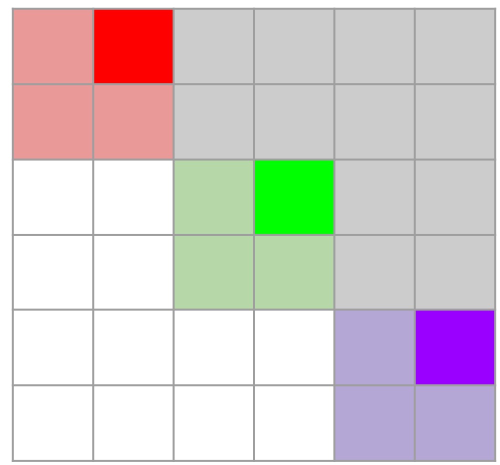
Effect on target trials

Alternative method
All utterances of the same speaker in one batch



Many but dependent

Used method
Generally 2 utterances per speaker in each batch



Fewer but less dependent

- Total weight of each speaker may change for the used method (and sets if their average number of utterances per speaker differs)
- In DPLDA experiments the alternative method did not work well

Memory issues in end-to-end system

- **f2s** processes frames. Number of intermediate values needed in training: #Frames*(360+1500+1500+1500+1500+2048)
- When **f2s** is trained independently, one frame from a many different utterances can be used
- For **e2e** we need many full utterances per batch so the number of frames is large
- We discard intermediate values from forward prop. of **f2s** and recalculate them during backprop. (Similar to Theano's `scan_checkpoints`)
- With this trick we can use around ~30 utterances per minibatch instead of ~5 on a GPU with 4GB
- The parameters (mainly the PCA matrix) of the network itself uses about 3GB

Results

Average of minDCF0.01 and minDCF0.005 =Joint training

System	UBM	i-extractor	PLDA	SRE16	PRISM Short	PRISM Long
Baseline	GMM	T	Gen.	0.988	0.699	0.411
Baseline DPLDA	GMM	T	Discr.	0.975	0.616	0.360
f2s	NN	T	Gen.	0.980	0.687	0.394
s2i	GMM	NN	Gen.	0.988	0.788	0.430
f2s+s2i	NN	NN	Gen	0.982	0.780	0.432
f2s+s2i+DPLDA	NN	NN	Discr.	0.953	0.597	0.300
s2i+DPLDA - joint *N*=5000	NN	NN	Discr.	0.936	0.586	0.287
All - joint, *N*=10	NN	NN	Discr.	0.936	0.587	0.289

Conclusions

- Neural networks can mimic estimation of responsibilities and i-vector extraction reasonably well
- Fine-tuning of the initialized network with binary cross-entropy criteria improves the performance
- Main improvement of joint training comes from refining of **s2i** module
  - **DPLDA** module does not change much
  - **f2s** module hard to train since we can use only small batches
- Future work:
  - Better joint training of the three blocks
  - Selection of suitable (difficult) training trials
  - Explore different training objectives, multiple enrollment sessions
  - Update PCA matrix and feature transform
  - Replace **f2s** with lighter network
  - Experiment with less constrained/regularized network

Thank you!

Questions?