

SPEAKER RECOGNITION IN THE WILD

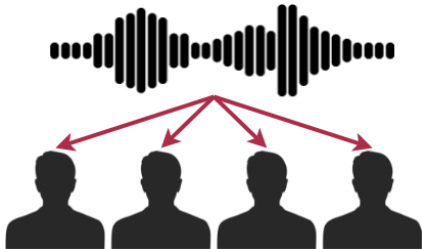
Audio Pattern Recognition Project

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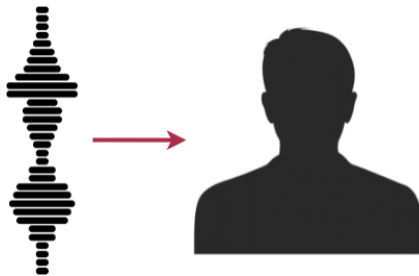
TASK OVERVIEW

Speaker Identification

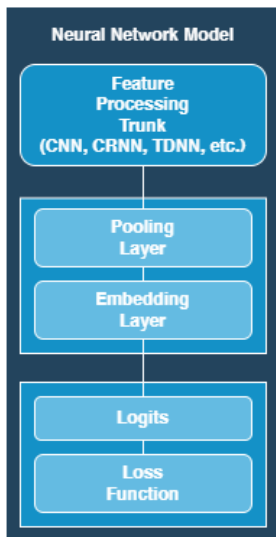


Who is the speaker?

Speaker Verification



Is this speaker A?



» **First block (“Trunk”)**

- › Takes as input acoustic features (MFCCs or Mel spectrograms) and outputs frame-level features

» **Second block**

- › Pooling layer to aggregate frame-level features of varying length into fixed dimensional utterance-level features
- › Fully connected layer to produce embeddings

» **Third block**

- › Projection into a dimension whose size is the number of speakers
- › Loss function

» **Scoring**

- › PLDA
- › Cosine distance

» **Score normalization**

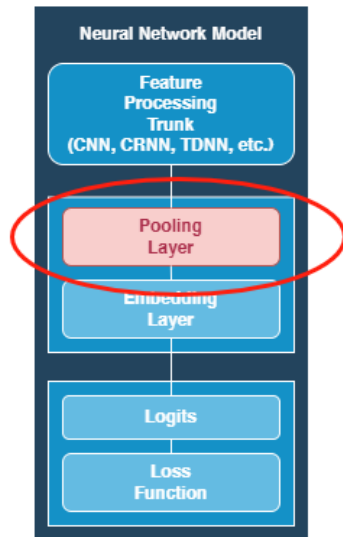
- › Adaptive S-Norm

» **Metrics**

- › EER
- › MinDCF

$$C_{\text{miss}} \times P_{\text{target}} \times P_{\text{miss}}(\theta) + C_{\text{fa}} \times (1 - P_{\text{target}}) \times P_{\text{fa}}(\theta)$$

- » **Temporal Average Pooling (TAP)**
- » **Self-Attentive Pooling (SAP)**
- » **Other Pooling Layers**
 - › Self Multi-Head Attention Pooling
 - › Attentive Statistics Pooling (ASP)



» **Softmax**

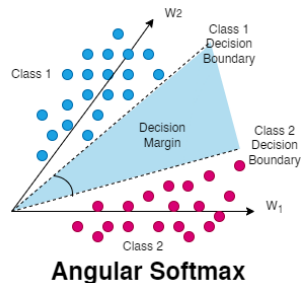
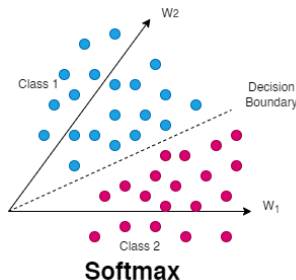
- › Does not enforce intra-class compactness and inter-class separation

» **Angular Additive Margin Softmax (AAM Softmax)**

- › Improves compactness and separation
- › Difficult to train with and sensitive to parameters

» **Sub-center Angular Additive Margin Softmax (SC AAM Softmax)**

- › More robust against noisy data



EXPERIMENT

» VoxCeleb1 Dataset

- › Collected “in the wild” from YouTube
- › Background noise, music, overlapping speech and varying room acoustics
- › Heterogeneous age, gender and nationality

» We used a subset due to hardware constraints

- › 100 speakers, retaining gender ratio
- › Official training, validation and test splits
- › For verification, 10 speakers not present in the training set

		Full Dataset	Identif. Set	Verif. Set
Speakers No.		1,251	100	10
Samples No.		153,516	13,042	758
Gender	<i>Male</i>	0.55	0.55	0.50
	<i>Female</i>	0.45	0.45	0.50
Nationality^a	<i>USA</i>	0.64	0.59	0.80
	<i>UK</i>	0.17	0.19	0.10
	<i>Canada</i>	0.04	0.02	-
	<i>Australia</i>	0.03	0.04	-
Seconds	<i>Mean</i>	8.25	8.20	8.05
	<i>Std</i>	5.31	5.35	5.14

^aOnly the four most frequent nationalities in the entire dataset are listed.

» **Features**

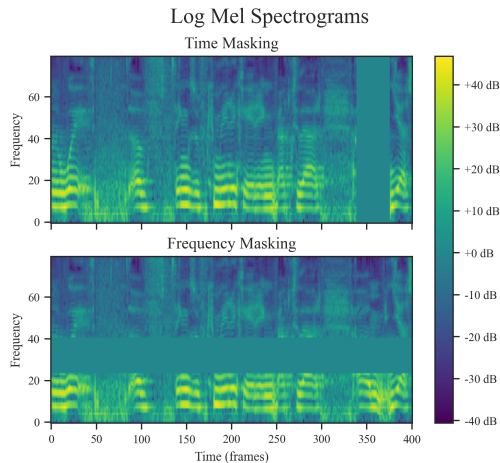
- › 80-dimensional log Mel spectrograms
- › Window length of 25 ms, frame-shift of 10 ms
- › Cepstral mean normalization

» **Offline data augmentation**

- › Speed perturbation
- › Background noise
- › Babble
- › Reverberation

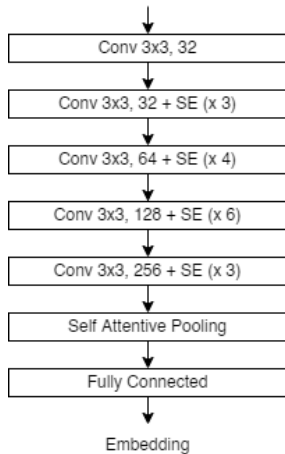
» **Online data augmentation**

- › SpecAugment: time and frequency masking

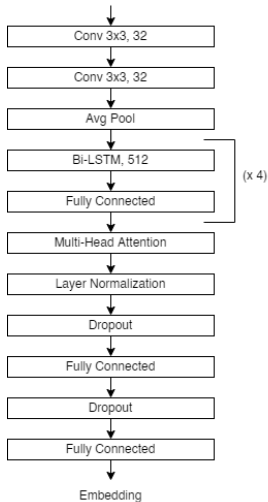


ResNet34-SE

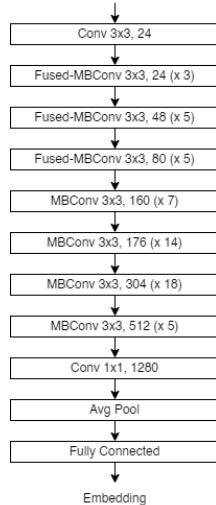
Log Mel Spectrogram

**LAS-MHA**

Log Mel Spectrogram

**EfficientNetV2**

Log Mel Spectrogram



» **Large Margin Fine-Tuning**

- › Training in two steps
- › Random crops: from 2 to 4 seconds
- › SC AAM Softmax: margin from 0.1 to 0.15, scale from 15 to 20
- › SpecAugment only in the first step

» **Evaluation**

- › Full-length utterances for verification
- › Random 4 seconds crops for identification

Model	Year	Training Set	Top1 Accuracy	Top5 Accuracy	F1 Score	EER(%)	MinDCF ^a
Nagrani et al.	2017	VoxCeleb1	80.50	92.10	-	-	-
Nagrani et al.	2017	VoxCeleb1	-	-	-	7.80	0.710 (0.01)
Cai et al.	2018	VoxCeleb1	89.90	95.70	-	-	-
Cai et al.	2018	VoxCeleb1	-	-	-	5.27	0.439
Cai et al.	2018	VoxCeleb1	-	-	-	4.46	0.577
Okabe et al.	2018	VoxCeleb1	-	-	-	3.85	0.406 (0.01)
Hajibabaei, Dai	2018	VoxCeleb1	94.60	98.10	-	4.69	0.453 (0.01)
Hajibabaei, Dai	2018	VoxCeleb1	92.80	97.50	-	4.30	0.413 (0.01)
Chunget al.	2019	VoxCeleb1	89.00	96.15	-	5.37	-
Chunget al.	2019	VoxCeleb1	89.00	95.94	-	5.26	-
Hajavi, Etemad	2021	VoxCeleb1	-	-	-	3.14	-
Thienpondt et al.	2021	VoxCeleb2	-	-	-	0.64	0.070 (0.01)
Thienpondt et al.	2021	VoxCeleb2	-	-	-	0.56	0.074 (0.01)
Zhao et al.	2021	VoxCeleb2	-	-	-	0.52	0.050 (0.01)
Zhao et al.	2021	VoxCeleb2	-	-	-	0.56	0.048 (0.01)
SVM (our baseline)	2022	VoxCeleb1 Subset	13.98	-	11.46	-	-
ResNet34-SE (ours)	2022	VoxCeleb1 Subset	64.21	84.21	59.28	14.50	0.893 (0.01)
LAS-MHA (ours)	2022	VoxCeleb1 Subset	47.97	66.62	42.94	21.69	0.980 (0.01)
EfficientNetV2 (ours)	2022	VoxCeleb1 Subset	67.67	85.11	64.26	16.44	0.974 (0.01)

^aIf provided by the Authors, we noted the P_{target} value within parentheses.

Thank You