

#### DUKE KUNSHAN UNIVERSITY

- Sino-US Joint Venture University with independent legal status
- Duke-standard education and research
- Comprehensive and small







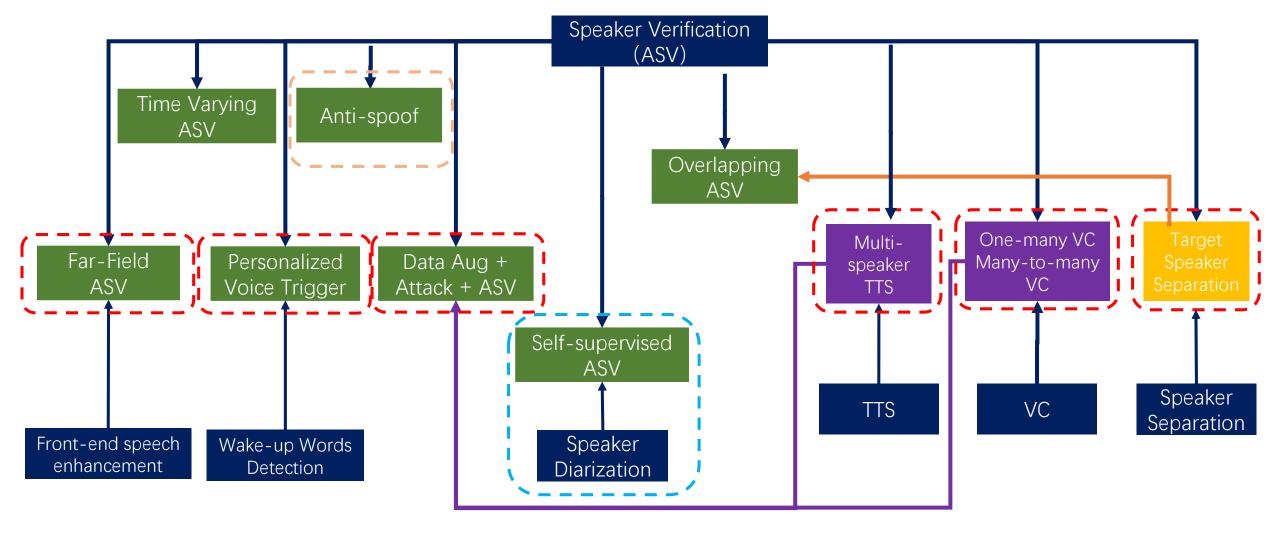




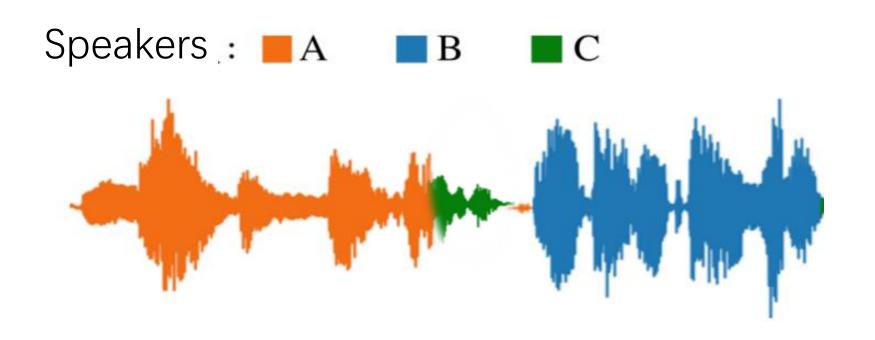


# Speaker Verification Related Research Topics





# Introduction of Speaker Diarization a Who-Spoke-When problem





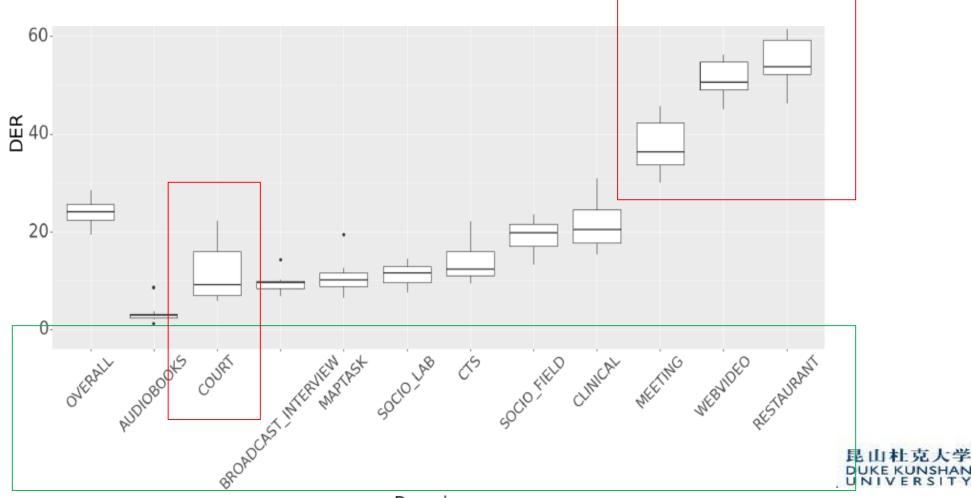
# Potential applications / Dihard3 test data

Domain	#Speakers	#Recordings	Duration of full set (h)	Duration of core set (h)	Overlap ratio (%)
Audiobooks	1	12	2.01	2.01	0
Broadcast interview	$3 \sim 5$	12	2.06	2.06	1.2
Clinical	2	48	2.06	4.27	4.8
Courtroom	$5 \sim 10$	12	2.08	2.08	1.9
CTS	2	61	2.17	10.17	13.6
Map task	2	23	2.53	2.53	2.9
Meeting	$3 \sim 10$	14	2.45	2.45	28.9
Restaurant	$5 \sim 8$	12	2.03	2.03	33.7
socio_field	$2\sim 6$	12	2.01	2.01	8.1
socio_lab	2	16	2.67	2.67	5.0
Web video	$1 \sim 9$	32	1.89	1.89	27.7
Total	=	254	23.94	34.15	12.2



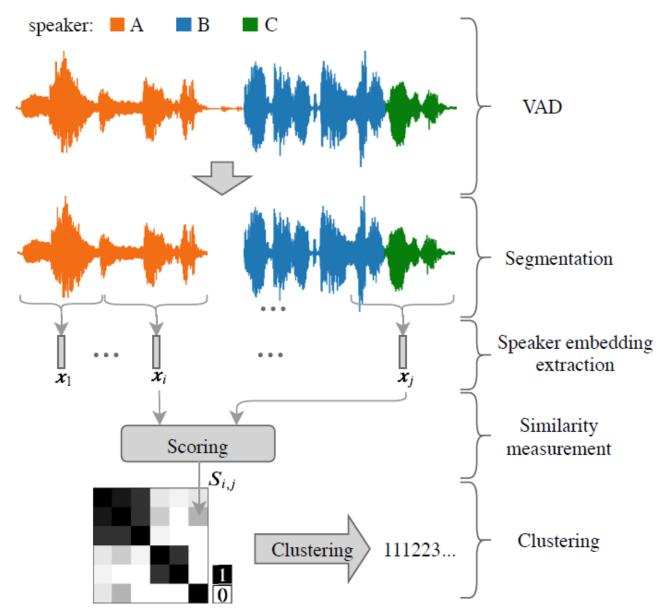


Potential applications / Dihard3 track 2 results



Domain

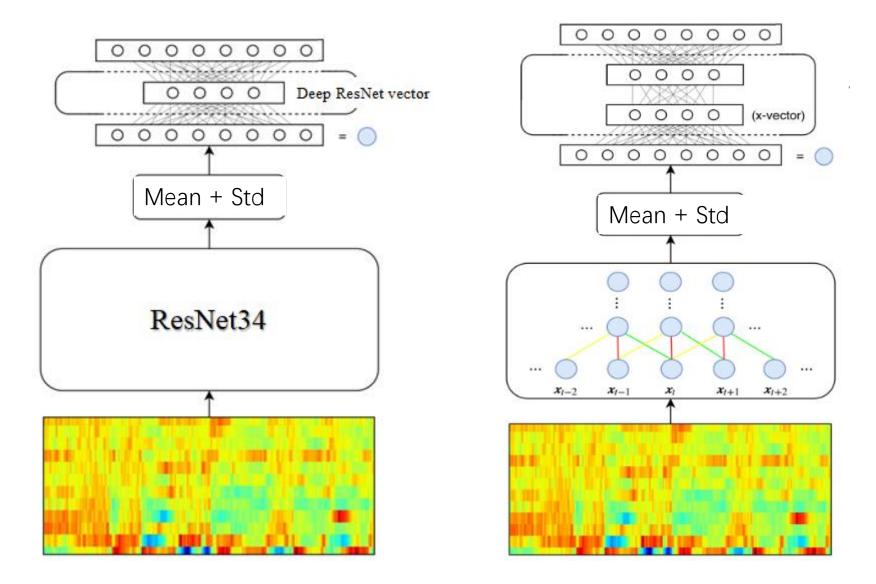
## Pipeline style modular system



VAD, Segmentation (speaker change point detection), Speaker embedding extraction (e2e SV), similarity measurement (PLDA modeling)

Are these models are trained in the supervised manner (except the clustering)

## Speaker Embedding Extraction

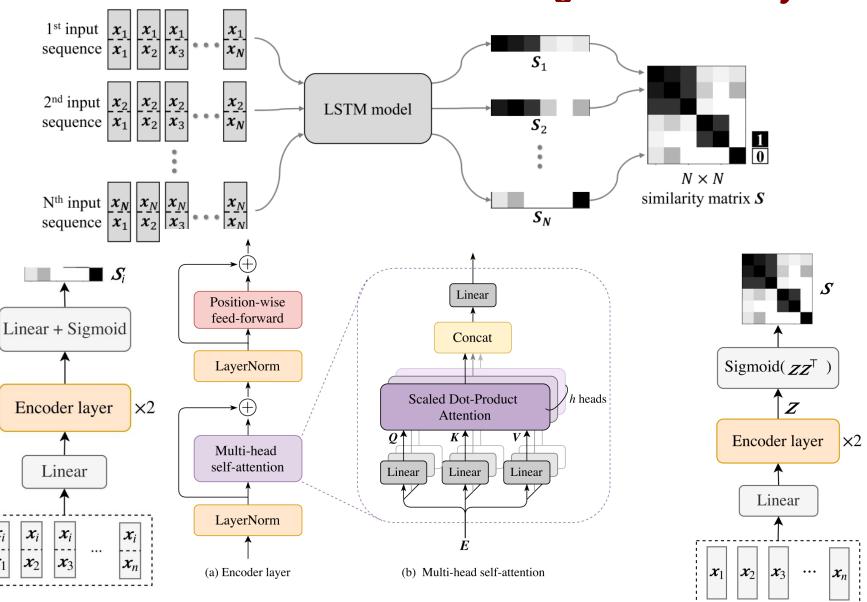


Snyder, David, Daniel Garcia-Romero, Gregory Sell, Daniel Povey, and Sanjeev Khudanpur. "X-vectors: Robust dnn embeddings for speaker recognition." Proc. of ICASSP, pp. 5329-5333, 2018. Cai, Weicheng, Jinkun Chen, and Ming Li. "Exploring the Encoding Layer and Loss Function in End-to-End Speaker and Language Recognition System." In Proc. Odyssey, pp. 74-81. 2018.

## Estimating the similarity matrix

#### LSTM based scoring

Qingjian Lin, Ruiqing Yin, Ming Li, Hervé Bredin and Claude Barras, "LSTM Based Similarity Measurement with Spectral Clustering for Speaker Diarization", Interspeech 2019.



Attention based scoring Qingjian Lin, Yu Hou and Ming Li, "Self-Attentive Similarity Measurement Strategies in Speaker

Diarization", Interspeech 2020.

Attention vector-to-sequence

Attention sequence-to-sequence

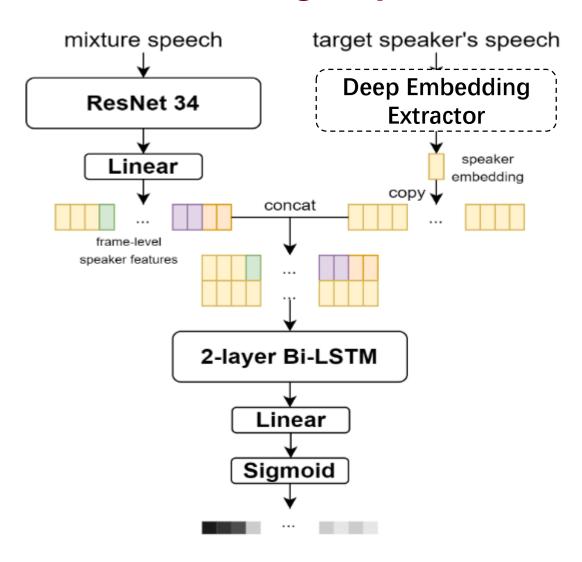
## Estimating the similarity matrix

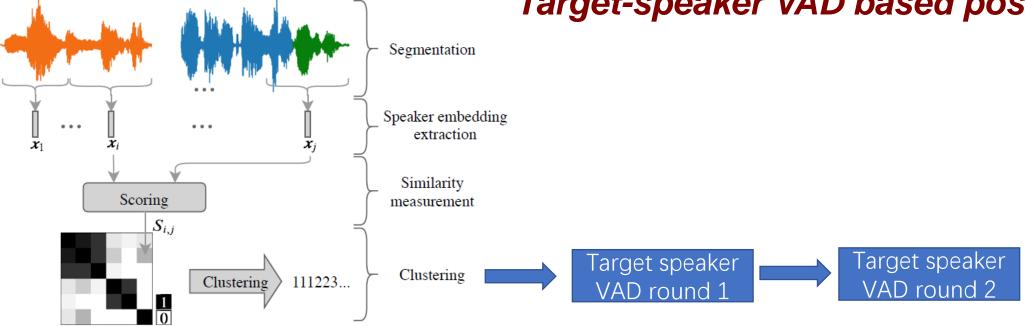
Results on Dihard II task 1

Table 2: Evaluation on DIHARD II corpus. Results are reported with and without domain adaptation by the Dev Set.

Model	+VB	De	ev	Ev	al	Eval + ad	laptation	Time cost (Eval)
		DER(%)	JER(%)	DER(%)	JER(%)	DER(%)	JER(%)	2333 (23.33)
LCTM	×	19.65	49.60	20.57	50.25	19.72	46.49	67 min
LSTM	$\sqrt{}$	19.48	49.21	19.98	49.42	19.26	45.91	-
Att-v2s	×	19.07	47.43	20.15	47.84	18.98	43.20	148 min
Att-v28	$\sqrt{}$	18.76	46.77	19.46	47.01	18.44	42.52	-
Att-s2s	×	19.39	48.42	21.46	48.71	21.45	43.19	24 s
Att-828	$\sqrt{}$	19.16	47.99	20.78	47.92	20.12	41.73	-
PLDA	×	23.48	57.17	-	-	23.73	56.84	51 s
	D.	IHARD II w	inner syste	m [27]		18.42	44.58	
	DI	HARD II of	ficial baseli	ne [28]		25.99	59.51	

Lin, et.al, "Self-Attentive Similarity Measurement Strategies in Speaker Diarization", Interspeech 2020.





Results on DIHARD3 CTS data

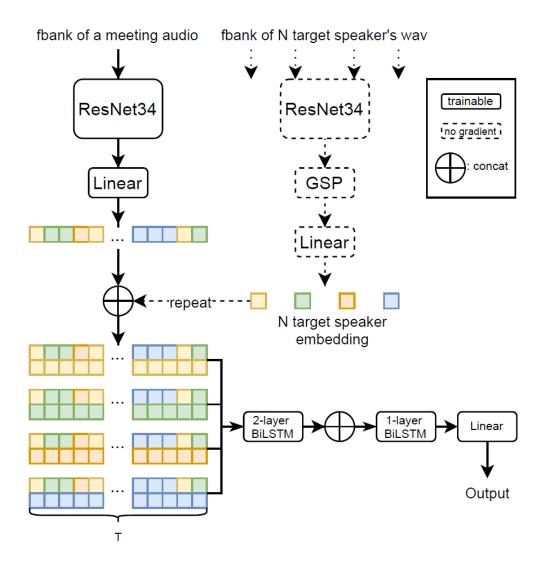
Training data	Finetune data	Testing data	Methods	DER
N/A	CTS-dev-41	CTS-dev-20	X-vector + Spectral Cluster	15.07%
SRE+SWBD	N/A	CTS-dev-20	+ target speaker vad round 1	10.60%
SRE+SWBD	CTS-dev-41	CTS-dev-20	+ target speaker vad round 1	7.80%
SRE+SWBD	CTS-dev-41	CTS-dev-20	+ target speaker vad round 2	7.63%

Weiqing Wang, Qingjian Lin, Danwei Cai, Lin Yang, Ming Li, "The DKU-Duke-Lenovo System Description for the Third DIHARD Speech Diarization Challenge Workshop, 2021

#### Results on DIHARD3 full test data

	Dataset	Method	DER on full set (%)	DER on core set (%)
Track1	NCTS (adapt) & CTS NCTS (adapt) & CTS (adapt)	att-v2s + SC & Cosine + AHC att-v2s + SC & TSVAD round 2	16.34 13.39	17.03 15.43
Track2	NCTS (adapt) & CTS NCTS (adapt) & CTS (adapt)	att-v2s + SC & Cosine + AHC att-v2s + SC & TSVAD round 2	18.90	21.63

## Another target-speaker VAD based post processing



Results on the fearless step challenge phase III dataset

Model	D	ev	Eval			
	Track 1	Track 2	Track 1	Track 2		
1 LSTM	21.48	13.56	-	-		
2 Att-v2s	22.57	15.11	-	-		
3 AHC (uni-seg)	20.83	13.33	-	-		
4 AHC (ahc-seg)	21.39	14.21	-	-		
5 TSVAD (round 0)	20.75	11.88	43.99	13.85		
6 TSVAD (round 1)	20.94	11.99	-	-		
Fusion (1+2+3+4)	20.39	12.70	44.56	14.63		
Fusion (1+2+3+4+5)	-	11.81	-	12.83		
Fusion (3+4+5)	19.19	11.40	42.21	12.32		

## New results

DER (%) OF DIFFERENT SIMILARITY MEASUREMENT MODELS. EMBD-AUG IS THE DATA AUGMENTATION PERFORMED ON THE SPEAKER EMBEDDING, SP IS SEGMENTAL POOLING, AND JT DENOTES JOINTLY TRAINING.

Model	DIHARD II			DIHARD III			VoxConverse			
	Dev	Eval	Eval (+dev adapt)	Dev	Eval	Eval (+dev adapt)	Dev	Eval	Eval (+dev adapt)	
BiLSTM	24.15	25.59	19.92	21.03	20.10	17.03	13.29	17.88	12.45	
+ embd aug	17.44	18.25	18.12	16.15	15.85	15.62	4.50	6.91	6.70	
+ SP	17.34	17.81	17.80	16.11	15.61	15.45	4.47	6.02	4.57	
+ JT	-	-	17.76	-	-	15.18	-	-	4.63	
Self-att	20.97	22.48	19.99	19.99	19.20	16.84	10.29	14.08	10.21	
+ embd aug	18.00	18.71	18.41	16.47	16.04	15.85	7.10	9.26	7.25	
+ SP	17.97	18.76	18.00	16.52	16.00	15.65	6.06	7.95	5.67	
Official baseline	-	-	25.99 [61]	-	-	19.25 [62]	-	-	-	
Winner system (Clustering)	-	-	18.42 [20]	-	-	15.47 [65]	-	-	-	

Weiqing Wang, Qingjian Lin, Danwei Cai, **Ming Li** (\*), "Segment-level Speaker Embedding Similarity Measurement in Speaker Diarization", submitted to IEEE/ACM Transactions on Audio, Speech, and Language Processing

## New results

## Winner of VoxSRC 2021 speaker diarization track

TABLE III
DER (%) OF THE SEGMENT-LEVEL TS-VAD MODELS ON EVALUATION DATASET (N=8, FULLY ASSIGNED)

Pooling Size		IARD II		DIHARD III				VoxConverse				
	MISS(%)	FA(%)	SpkErr(%)	DER(%)	MISS(%)	FA(%)	SpkErr(%)	DER(%)	MISS(%)	FA(%)	SpkErr(%)	DER(%)
s=1 (80ms)	8.2	0.7	7.6	16.48	6.6	0.7	4.4	11.62	1.0	0.2	3.7	4.95
s=2 (160ms)	8.1	1.4	7.7	17.20	6.1	1.6	4.4	12.09	1.0	0.2	3.8	5.04
s=4 (320ms)	8.1	1.4	8.3	17.83	6.3	1.8	4.9	12.97	1.0	0.3	3.5	4.72
s=8 (640ms)	8.2	1.7	9.2	19.06	6.7	2.1	5.9	14.67	1.0	0.3	3.6	4.78
Clustering	9.7	0.0	8.1	17.76	9.5	0.0	5.7	15.18	1.6	0.0	3.0	4.57
Winner System (TS-VAD)	-	-	-	-	-	-	-	12.30 [65]	-	-	-	-

TABLE IV

DER (%) OF THE SEGMENT-LEVEL TS-VAD AS OVERLAP DETECTION ON EVALUATION DATASET (N=2, PARTIALLY ASSIGNED OVERLAPPED REGION)

Pooling Size		DIH	ARD II		DIHARD III				VoxConverse			
	MISS(%)	FA(%)	SpkErr(%)	DER(%)	MISS(%)	FA(%)	SpkErr(%)	DER(%)	MISS(%)	FA(%)	SpkErr(%)	DER(%)
s=1 (80ms)	8.0	1.0	8.1	17.19	5.7	1.5	5.7	12.89	1.1	0.3	3.1	4.39
s=2 (160ms)	7.9	2.1	7.9	17.94	5.4	2.8	5.4	13.57	1.0	0.5	3.0	4.49
s=4 (320ms)	8.2	1.9	7.9	17.98	5.7	2.8	5.3	13.77	1.1	0.3	3.0	4.40
s=8 (640ms)	8.3	1.7	8.0	18.00	6.2	3.1	5.3	14.49	1.0	0.5	3.0	4.52
Clustering	9.7	0.0	8.1	17.76	9.5	0.0	5.7	15.18	1.6	0.0	3.0	4.57

Weiqing Wang, Qingjian Lin, Danwei Cai, **Ming Li** (\*), "Segment-level Speaker Embedding Similarity Measurement in Speaker Diarization", submitted to IEEE/ACM Transactions on Audio, Speech, and Language Processing

# **Modularized Online Speaker Diarization**

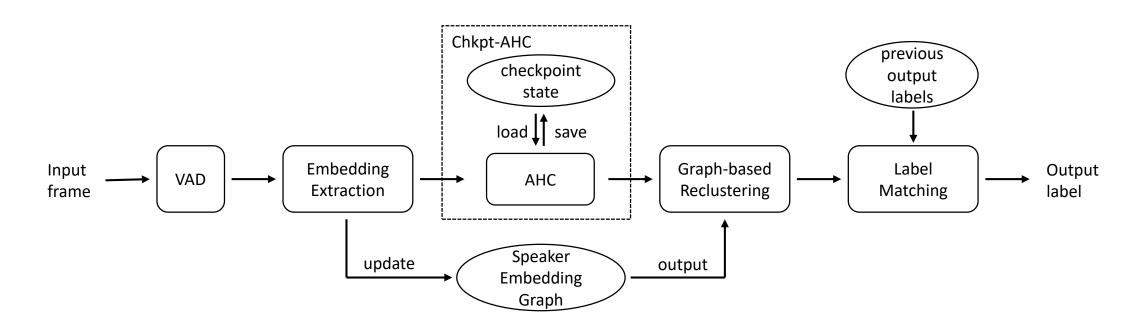


Fig 1 The pipeline of the purposed system

Yucong Zhang, Qinjian Lin, Weiqing Wang, Lin Yang, Xuyang Wang, Junjie Wang, Ming Li, "Online speaker diarization with graph-based label generation", submitted to ICASSP 2022.

# **Chkpt-AHC**

#### Problem:

 Agglomerative hierarchy clustering causes high time complexity

#### Solution:

- Save the intermediate state of AHC
- Starting from limited number of clusters

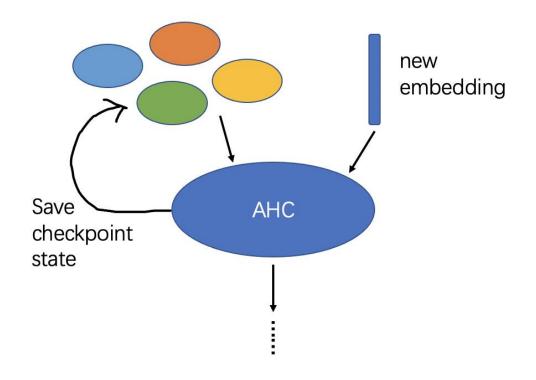


Fig 2 chkpt-AHC

# **Graph-based Reclustering**

### Speaker embedding graph

- Nodes represent speaker embeddings, N = {n<sub>A</sub>,n<sub>B</sub>,...,}
- Node  $n_K$  and  $n_L$  has edge  $e_{KL}$  if similarity between embedding K and L greater than pre-defined threshold  $\theta$ , weight equals the similarity
- Graph pruning to reduce the time complexity

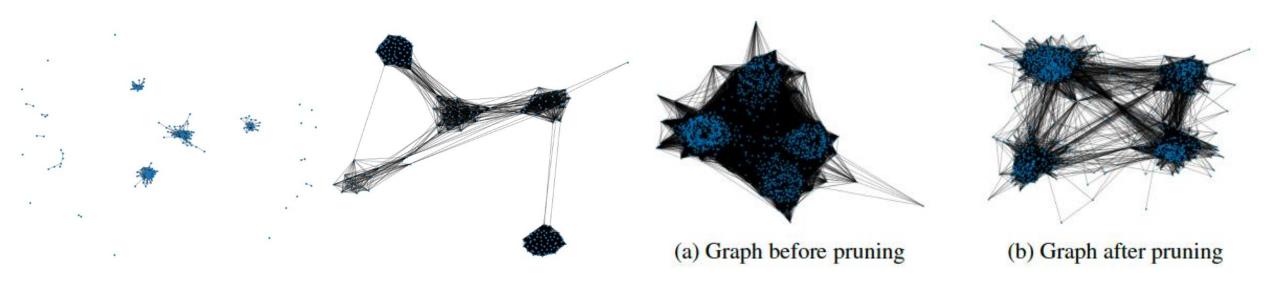


Fig 3 speaker embedding graph (threshold: left 0.6, right 0.3)

Fig 4 Effects of Graph pruning with threshold=0.3

# **Graph-based Reclustering**

#### Problem:

 After chkpt-AHC, due to high stopping criteria, lots of small clusters left behind

#### Solution:

- Use smaller threshold to build speaker embedding graph
- Assign remaining embeddings to speaker clusters based on cluster likelihood

$$\mathcal{L}_{C_j}^{(i)} = \frac{\sum_{n_k \in C_j} w_{ik}}{|C_j|}$$

where  $C_j$  represents j<sup>th</sup> speaker cluster,  $w_{ik}$  represents the weight of edge  $e_{ik} \in E$ 

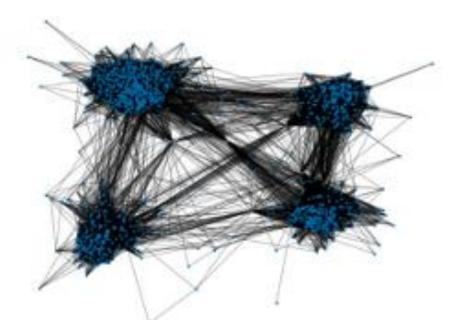


Fig 5 speaker embedding graph

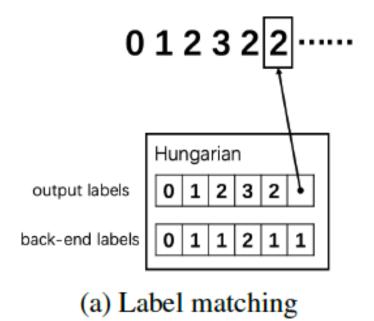
# **Label Matching**

#### Problem:

Label consistency

#### Solution:

- Construct bipartite graph
- Hungarian Algorithm



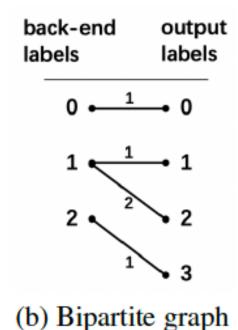


Fig 4 Label matching with Hungarian Algorithm

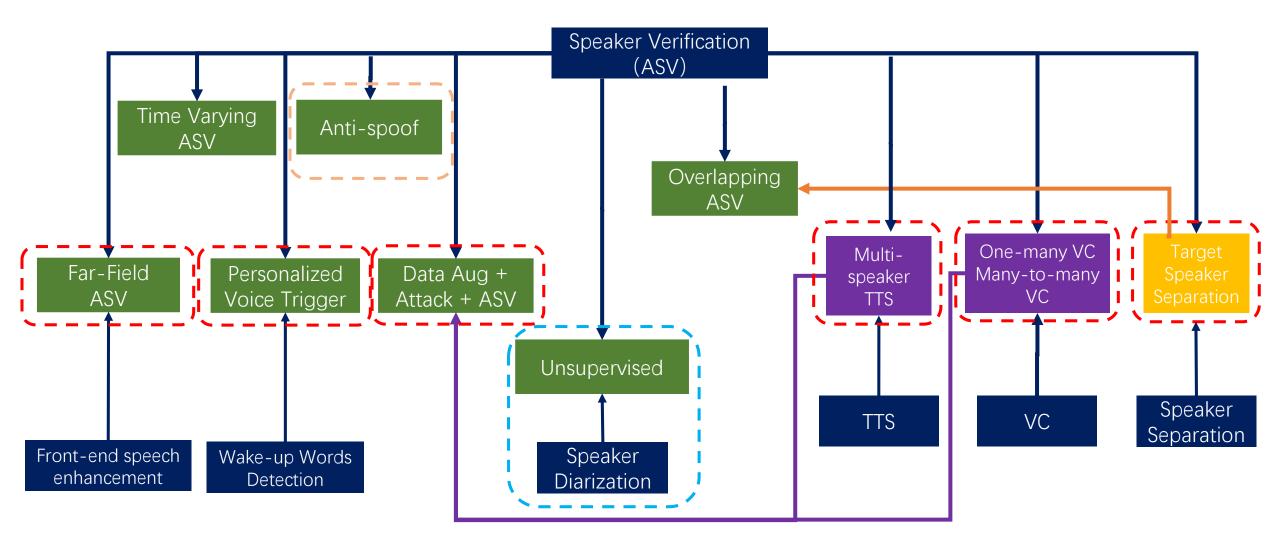
## **Results**

Table 1. The DER (%) of the proposed speaker diarization system. The baseline system is introduced by [23] for DIHARD3 competition without VB-HMM resegmentation. System 1 is the offline version of our proposed diarization system.

System	Offline	Online	AHC	Chkpt-		Graph-based	1		VoxConverse	
D J Stelli				AHC	Reclustering	Reclustering	Dev	Eval	Dev	Eval
Baseline	√	-	-	-	-	-	20.71	20.75	-	-
1	<b>√</b>	-	√	-	<b>√</b>	-	17.63	16.82	3.94	4.68
2	-	$\checkmark$		-	$\checkmark$	-	20.17	19.68	5.20	6.28
3	-	<b>√</b>	-	<b>√</b>	<b>√</b>	-	20.78	20.05	5.91	6.71
4	-	$\checkmark$	-	$\checkmark$	_	$\checkmark$	20.28	19.57	5.80	6.60

## Review





# Thank you very much!

ming.li369@duke.edu https://scholars.duke.edu/person/MingLi



