The HCCL System for Semi-Supervised Domain Adaptation task of VoxSRC22

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Overview

- Pseudo-labeling framework
  - Base model training with source labeled data
  - Embedding domain adaptation
  - Pseudo label generation
  - Model training with labeled source domain data and pseudo-labeled target domain data
  - Pseudo-label correction and retraining
- Supervised learning and self-Supervised learning

Base model training & Adaptation

- Base model training
  - Using models with as much variance as possible, either in terms of model structure or the training Protocol.

mdl	loss	vox2-train	t3-dev-EER ini	t3-dev-EER adapt
se-resnet34-32	circle	clean-fb64-sgd	16.86	14.29
cotnet	circle	clean-fb64-sgd	16.65	14.55
conformer	circle	aug-fb80-adam	16.95	14.14
ecapa-large	circle	aug-fb80-adam	18.02	14.62
se-resnet101-32	circle	aug-fb80-adam	14.06	11.90

- Adaptation
  - Aligning statistics between different domains
  - Aligning domain centers is easy and efficient, but aligning the variances need backends (LDA & PLDA)
  - We will explore variances alignment systematically in the future

Pseudo label generation

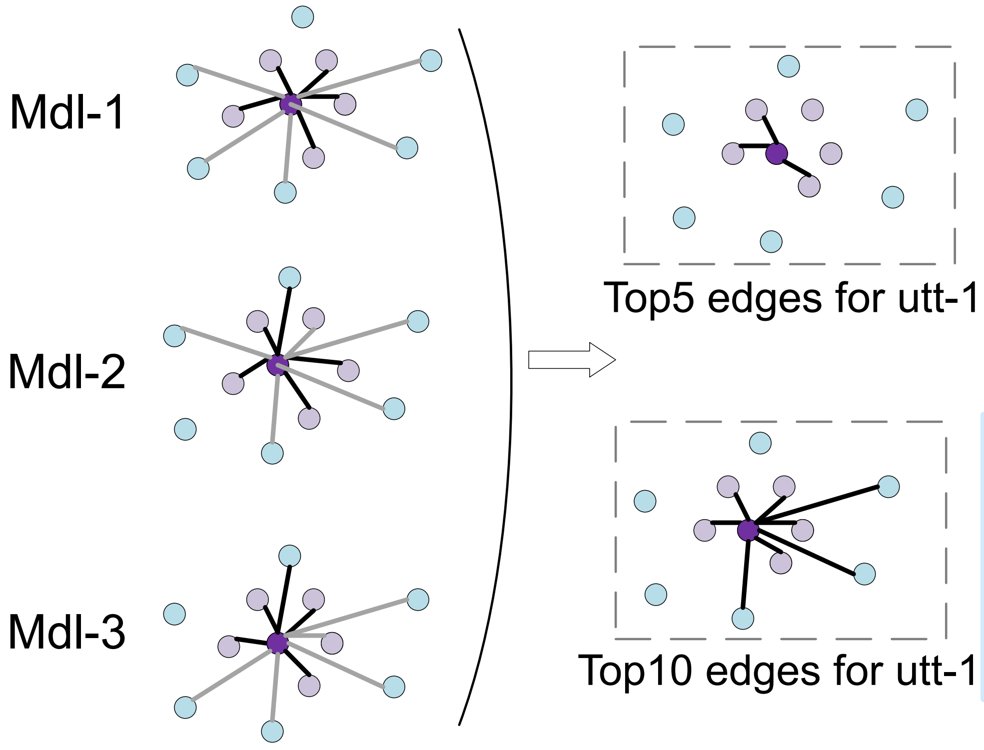
- Clustering algorithm :

  (a **progressive sub-graph** clustering algorithm based on **two Gaussian fitting** and **multi-model voting**)

- Key points:
  - finding high-confidence positive trials using a multi-model voting strategy based on the KNN affinity graph
  - utilizing connected sub-graphs to obtain pseudo labels
  - using iterative top-k information to gradually combine sub-classes
  - two Gaussian distributions fitting the intra-class score distribution to check for high-confidence edges

Pseudo label generation

High-confidence edges:

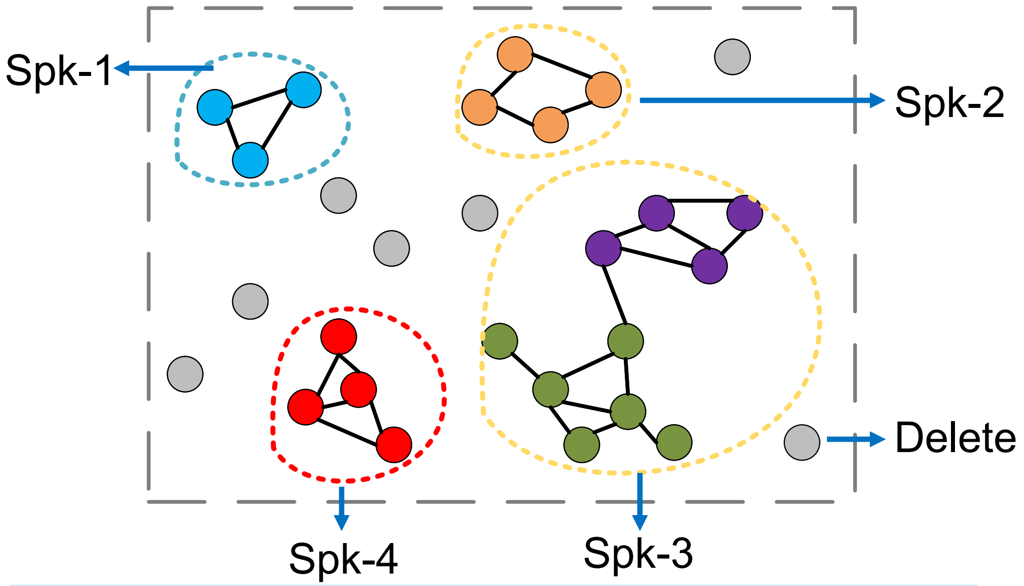


Notes1:
Whether or not to preserve edges also depends on similarity

Notes2:
Voting strategy can greatly decrease false positive rate

Constructing k-nearest neighbors graphs for utt-1 by voting

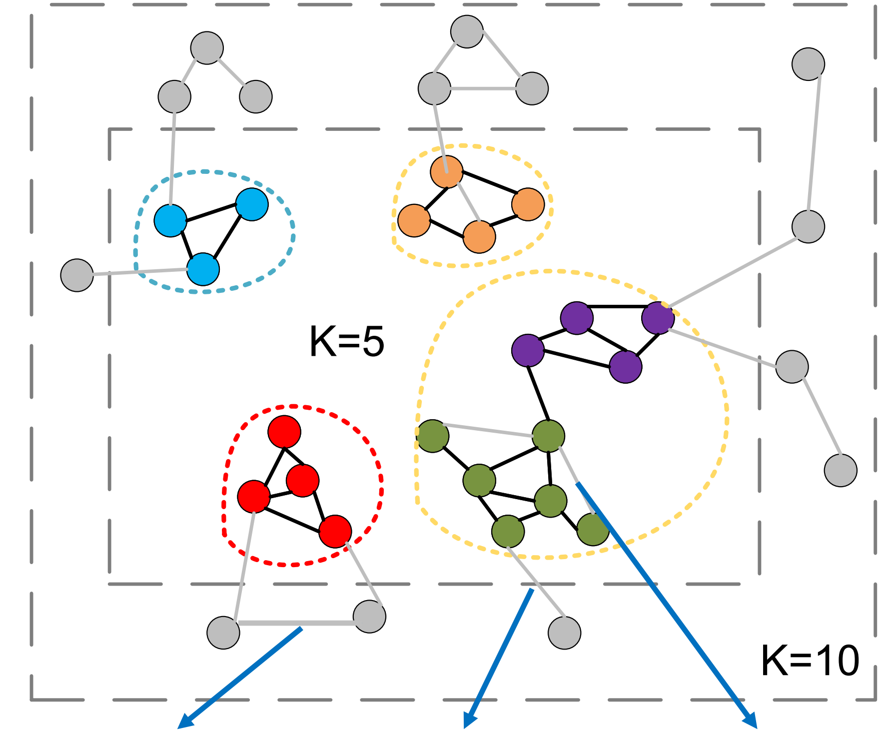
Connected sub-graphs:



Notes3:
Using connected sub-graph can greatly increase the intra-class diversity

Pseudo label generation

☐ Progressive :

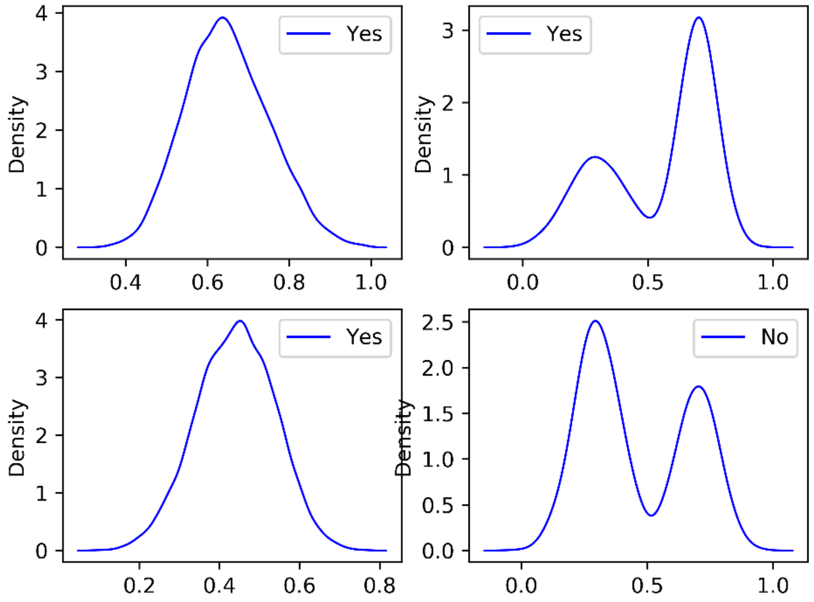


Edges_{new.new} Edges_{new.old} Edges_{old.old}

Notes1:
Preventing disastrous classes caused by error edges

☐ Two Gaussian fitting:

Cal similarity between all utts if combine



Notes1:
proper noisy label is okay

$\mu_1, \sigma_1, w_1; \mu_2, \sigma_2, w_2;$
represents parameters
max and min gaussian

$\mu_2 > th_{nm}$ *OR*
$w_1 > 0.5$ *OR*
$\mu_1 - \sigma_1 < (\ \mu_2 + \sigma_2) + \epsilon$

Model training with labeled source domain data and pseudo-labeled target domain data

- Stage 1
  - Subcenter is extremely important
  - Speed perturbation augmentation is used in all data
  - Both train the model from scratch and utilize models from Track1 as the pre-trained model are okay
  - For the latter, freezing the extractor in the beginning to make models be converged is necessary.
- Stage 2
  - CN-Celeb data without speed perturbation is used to finetune.
  - The VoxCeleb weights of the classification layer are preserved to prevent overfitting.
  - Expand chunksize to 6s and slightly increase constraint is effective

Pseudo-label correction and retraining

Error labels:

- 1label-vs-multispk (noisy labels)
- multilabel-vs-1spk (multi labels)

noisy labels:

- Subcenter is enough to correct

multi labels:

- Cal similarity of all audio in CN-Celeb to the two most similar class centers; denoted as s_i^1 and s_i^2;
- Split audios: s_i^1>0.5 and s_i^2<0.4 high-confidence; s_i^1>0.5 and s_i^2>0.4 median-confidence;
  s_i^1 < 0.5 low-confidence;
- Use audio with median-confidence to find ***multi labels***,
- Use the overlap between two labels to determine whether two labels need to be merged,
- Filter out audio that is low confidence, other audio is labeled by using predicted posterior probability.

Results and calibration

Table 4: *Results of systems for Track3. v0 means pseudo labels before correction, and v1 means after.*

	mdl	loss	train	t3-dev-EER	
				ini	calib
S1	Res2Net50	circle	v0-sgd	**8.45**	8.20
S2	ResNet34	circle	v0-sgd	8.61	**7.66**
S3	ECAPA-X4	circle	v0-sgd	9.57	8.81
S4	ECAPA-X4	circle	v0-adam	10.47	9.65
S5	ECAPA-X4	circle	v1-sgd	8.78	8.42

Table 5: *Results of systems that we submitted*

mdl	mode	dev-EER	eval-EER
S1	ini	8.45	8.07
S2	ini	8.61	8.64
S1+S2	ini	8.01	7.57
S1+S2+S3+S4	ini	7.87	7.40
S1+S2+S3+S4+S5	calib	**6.77**	**7.03**

Supervised&Self-Supervised Domain Adaptation

- Self-supervised learning requires no label
- Use supervised learning on labeled data, self-supervised learning on all data
- For supervised learning, we used circle loss; for self-supervised learning, we adopted DINO loss
- After pseudo-labeling, extract embeddings, averaged speaker-wise and appended after classification layer weights, continue training

Results

Table 3: *SSL-Assissted Domain Adaptation Results*

Data	Loss	Vox22-dev-t3	
		EER	$\mathrm{minDCF}_{0.05}$
Vox2dev	Circle	13.430	0.4848
Vox2dev+Track3	Circle+DINO	11.995	0.5160
Vox2dev+Track3-PL	Circle+DINO	10.055	0.4414

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Thanks