Prototypical Networks for Small Footprint Text-independent Speaker Verification

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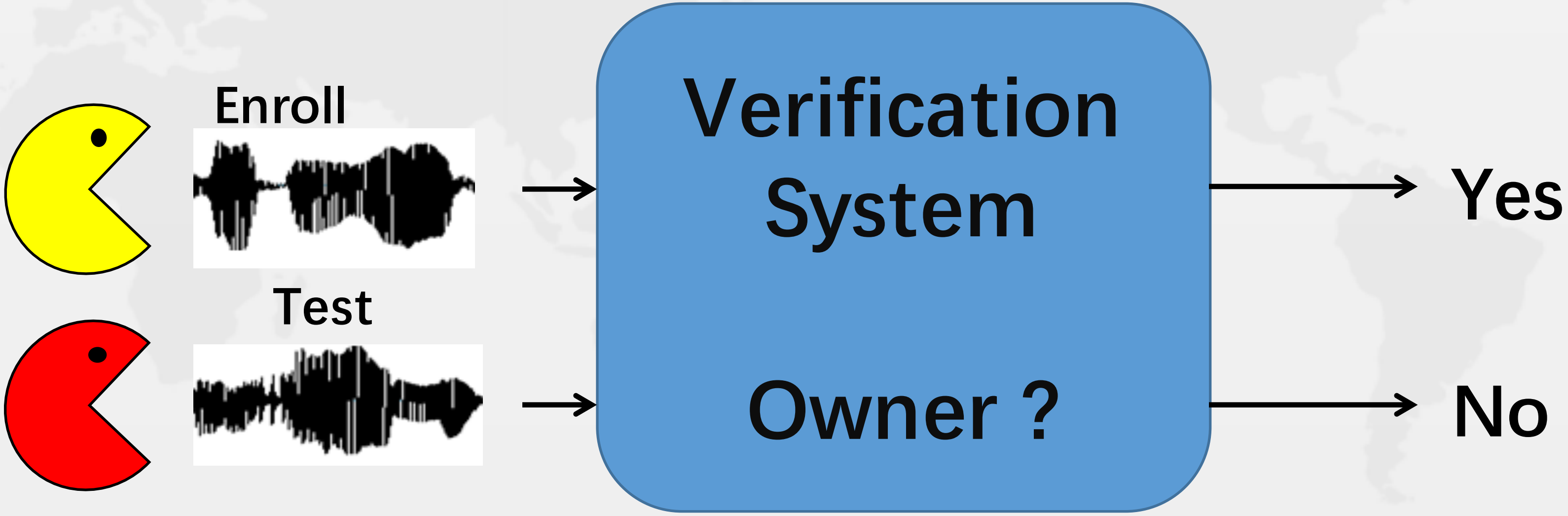
ICASSP 2020

Motivation

- There is a mismatch of the training objective between the front-end DNN and the PLDA backend in the speaker embedding approaches.
- Prototypical Networks aim at learning a non-linear mapping from the input space to an embedding space with a predefined distance metric. It tries to minimize the intra class distance and maximize the inter class distance, just like PLDA.
- It is worth to investigate the use of prototypical networks in a small footprint text-independent speaker verification task.

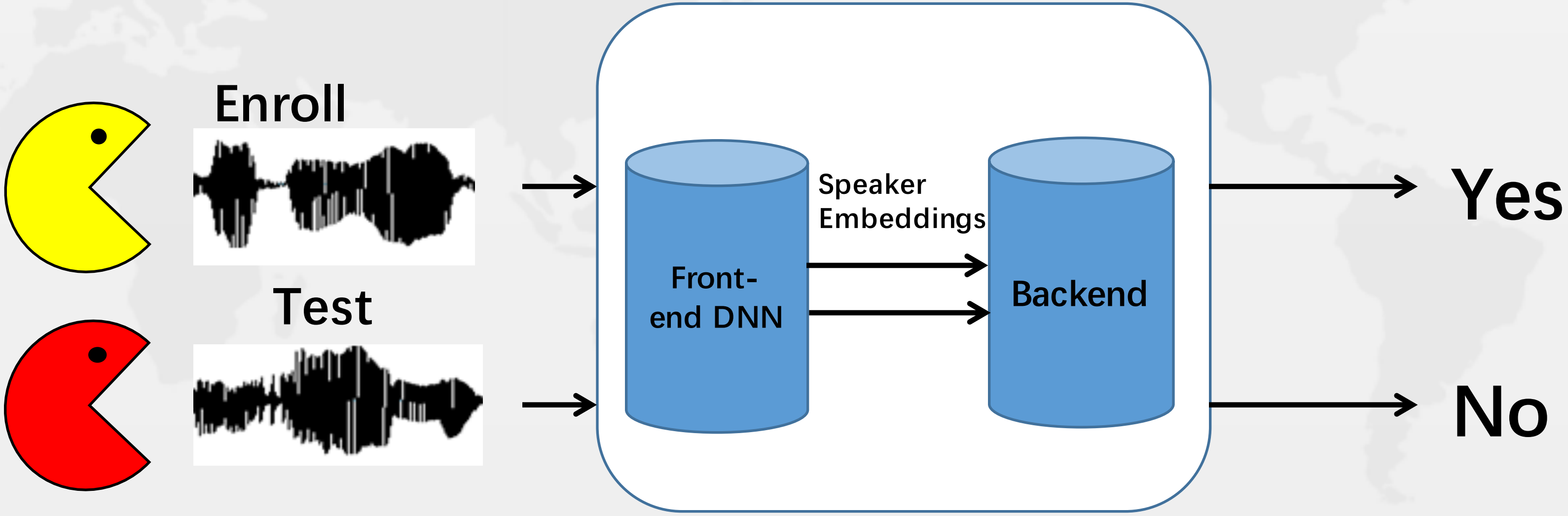
Text-independent Speaker Verification

- It needs to verify if the test speaker and enroller speaker are the same one.



The Speaker Embedding Approach

- Front-end DNN for speaker embedding extraction.
- Backend for similarity measure.

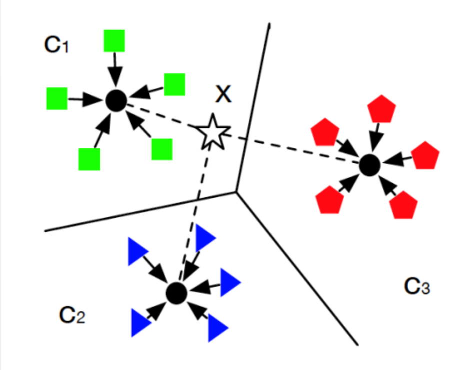


Meta-learning

- It becomes the most popular solution for solving few-shot classifications.
- Also known as 'learning to learn', aims to learn new skills or adapt to new environments rapidly with only a few examples.
- Many elegant solutions are proposed:
  - Matching Networks
  - Prototypical Networks
  - Model-agnostic Meta-learning

Prototypical Networks

- To train a model which can generalize to new classes not seen in the training set , given only a few examples per new class. Thus, it has to **learn a good representation**.
- It tends to minimize the intra class distance and maximize the inter class distance.
- The distance metric can be defined in a flexible way.



Jake Snell, Kevin Swersky, and Richard Zemel. "Prototypical networks for few-shot learning." In: *Advances in neural information processing systems*. 2017. p. 4077-4087.

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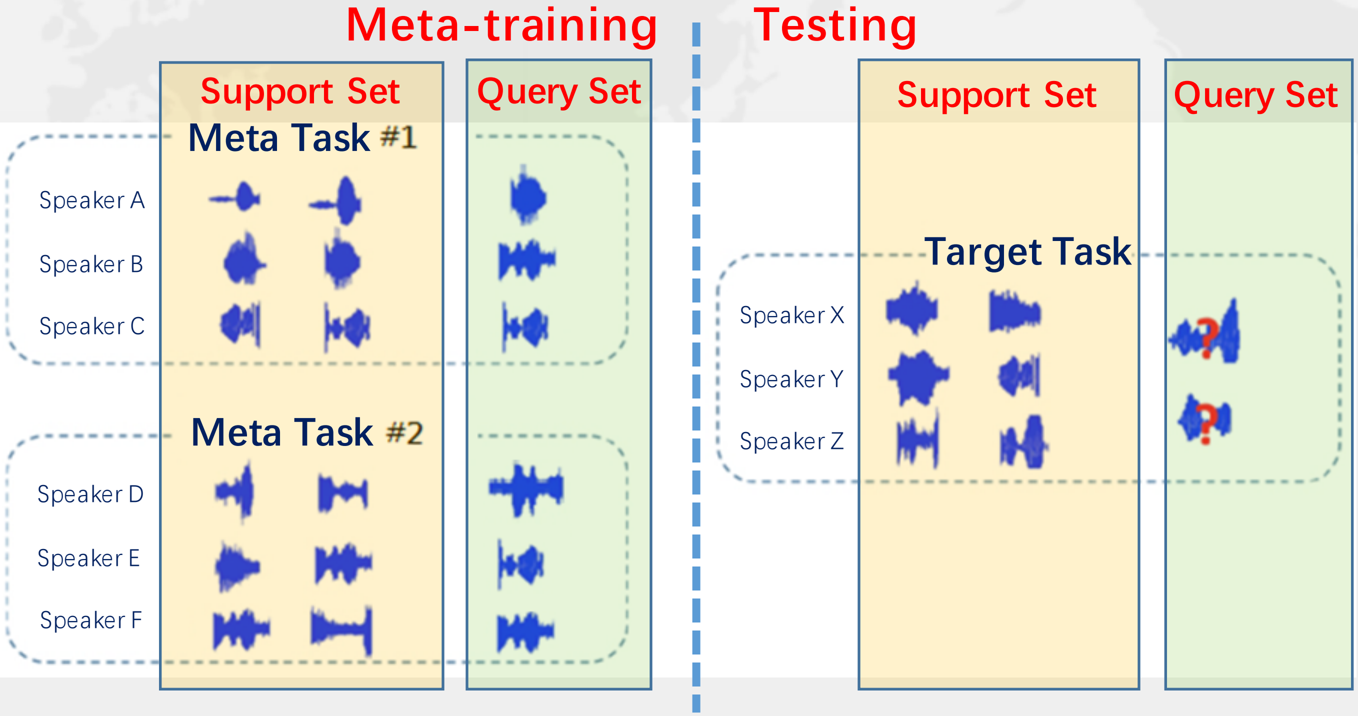
Meta-training in Few-shot Classification

- The model is trained on a number of meta-tasks and it treats an entire task as a training example.



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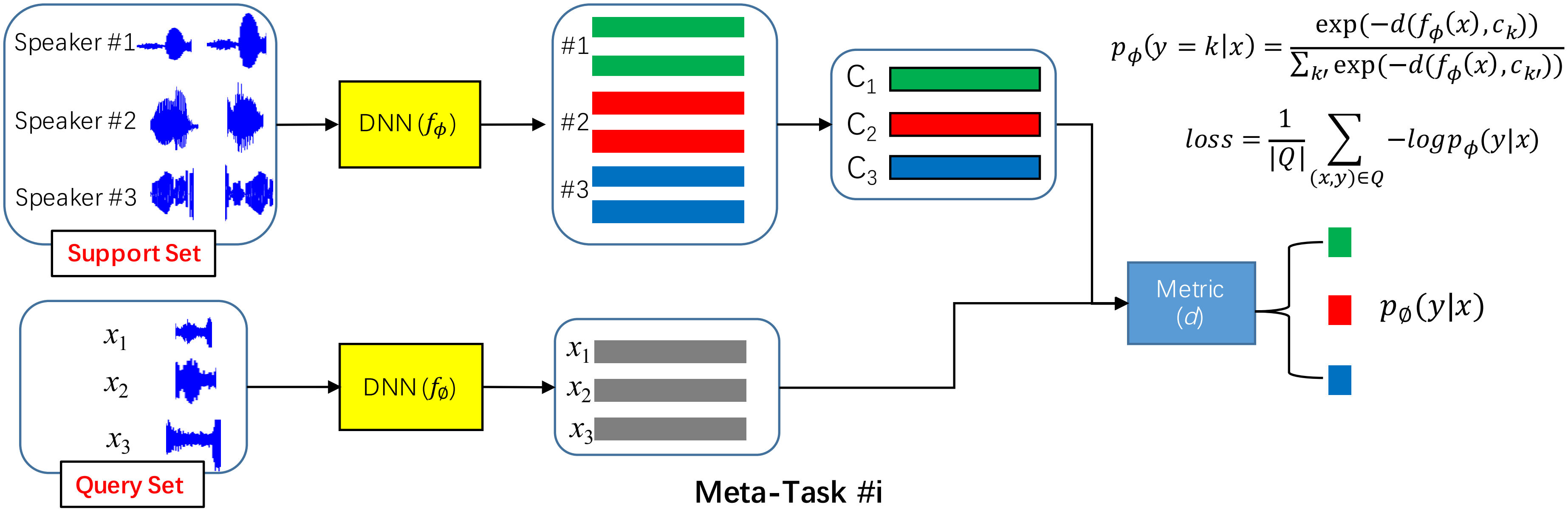
Prototypical Networks as the SV Frontend

- Support sets are used for computing class centroids.



The learned DNN will be used as the frontend

Experimental Setup

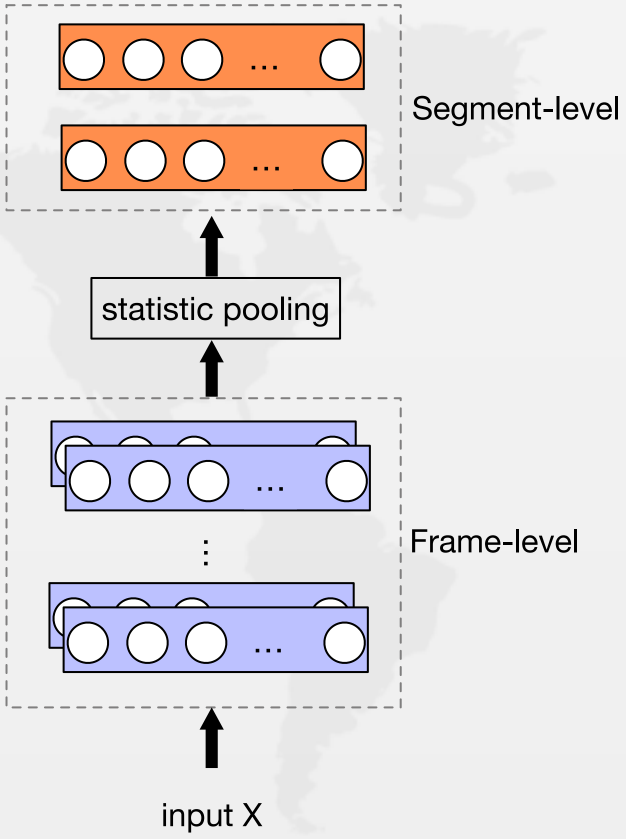
- Training data
  - SWBD dataset: 28k recordings from 2.6k speakers
  - SRE dataset: 35k recordings from 3.8k speakers

  - *4k_full*, *4k_2utt*, *2k_2utt* are sampled to compare the proposed method and the conventional one.
- Evaluation data
  - SRE10

  - Both the enrollment and test utterances are truncated to the first $T \in \{2,5,10,30\}$ seconds of speech, as determined by an energy-based VAD.

Model Structure

- We use a similar model structure as the X-vector* approach.
- Several layers are removed to fulfill the small footprint requirement.
- We compare our approach with the conventional learning approach.



*David Snyder, Daniel Garcia-Romero, Gregory Sell, Daniel Povey, and Sanjeev Khudanpur, "X-vectors: Robust DNN embeddings for speaker recognition," in IEEE International Conference on Acoustics, Speech and Signal Processing, 2018.

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Practical Implementation of Prototypical Networks

- Our work has a large number of speakers within each meta-task, which costs a high memory usage. To address this problem, we design an expectation-maximization (EM) like algorithm which save the memory cost and does not affect the performance.
- In the E step, the embeddings of the support set are extracted and the class centroids are estimated.
- In the M step, the embeddings of the query set are extracted, then the distances and the losses are estimated.

Baseline

- Conventional learning approach with different backend metrics

Table 1. *EER(%) of a conventional front-end with different backend metrics. The models are trained with 2k_2utt training set.*

Backend Metric	2s-2s	5s-5s	10s-10s	30s-30s
Euclidean	45.85	46.07	45.85	46.48
Cosine	46.14	46.00	46.02	46.76
LDA+Euclidean	41.23	34.54	29.90	23.04
LDA+Cosine	36.66	28.77	21.94	15.32
LDA+PLDA	**34.51**	**26.26**	**18.39**	**12.27**

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Results

- Prototypical networks with different backend metrics

Table 2. *EER(%) of prototypical embeddings (10-shots) on SRE10. The models are trained with the 2k_2utt training set.*

Front-end Metric	Backend Metric	2s-2s	5s-5s	10s-10s	30s-30s
Euclidean	Euclidean	40.94	34.50	30.06	26.01
Euclidean	LDA+Euclidean	43.66	38.57	33.19	27.29
Euclidean	LDA+PLDA	34.34	25.70	18.62	11.81
Cosine	Cosine	36.07	29.39	25.72	23.17
Cosine	LDA+Cosine	36.88	28.52	21.62	14.94
Cosine	LDA+PLDA	**33.42**	**24.59**	**17.37**	**10.97**

Results

- Comparing prototypical networks and baseline approach

Table 3. *EER(%) on SRE10 with various training set*

Training set	System	2s-2s	5s-5s	10s-10s	30s-30s
$2k\_2utt$	Baseline	34.51	26.26	18.39	12.27
	Cosine	**33.42**	**24.59**	**17.37**	**10.97**
$4k\_2utt$	Baseline	33.47	24.98	17.44	11.61
	Cosine	**32.17**	**22.77**	**15.46**	**9.66**
$4k\_full$	Baseline	**29.79**	21.48	13.96	**8.52**
	Cosine	30.14	**21.28**	**13.75**	8.55

Observations

- The prototypical networks are better than the conventional approach when the front-end is directly evaluated with Euclidean or Cosine distance.
- LDA brings negative impact when Euclidean distance is used while it does not bring negative impact to Cosine distance.
- When there are **limited amount of training data per speaker**, prototypical networks perform obviously better than the baseline approach. When the entire training set is used, the two approaches obtain similar performance.

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Future Work

- In this paper, we apply the prototypical networks to improve the front-end in the speaker embedding approach.
- In the future, we want to further exploit the meta-learning framework to implement an end-to-end speaker verification system.
- Improve the overall performance with data augmentation techniques.
- Explore other meta learning methods.

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Thank you!