Meta-Learning for Short Utterance Speaker Recognition with Imbalance Length Pairs

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Abstract

In realistic settings, a speaker recognition system needs to identify a speaker given a short utterance, while the utterance used to enroll may be relatively long. However, existing speaker recognition models perform poorly with such short utterances. To solve this problem, we introduce a meta-learning scheme with imbalance length pairs. Specifically, we use a prototypical network and train it with a support set of long utterances and a query set of short utterances. However, since optimizing for only the classes in the given episode is not sufficient to learn discriminative embeddings for other classes in the entire dataset, we additionally classify both support set and query set against the entire classes in the training set to learn a well-discriminated embedding space. By combining these two learning schemes, our model outperforms existing state-of-the-art speaker verification models learned in a standard supervised learning framework on short utterance (1-2 seconds) on VoxCeleb dataset. We also validate our proposed model for unseen speaker identification, on which it also achieves significant gain over existing approaches. Index Terms: speaker verification, speaker identification, meta-learning, short duration, text-independent, open-set

1. Introduction

Speaker recognition (SR) with short utterance is an important challenge in realistic setting as test utterance may short. While the recent advances in deep learning make it possible to get impressive performance on speaker recognition such as speaker verification (SV) and identification (SI), it still remain challenging in the actual setting (e.g. short duration, unseen speaker SI). As these issues grow in importance, some of the works are proposed to deal with these problems. For the SR with short utterance, [1][2] introduce task-specific feature extractor to extract as much information from short utterance. [3][4] introduce aggregation method to attend for informative frames from output of feature extractor. In addition to these approaches, various attempts have been made to deal with short utterance. However, many of them do not provide a fundamental solution to the real situation.

In this work, we aim to tackle this problem by meta-learning with imbalance length pair. Specifically, we organize episode with support set of long utterance and query set of relatively short utterance. By optimizing sequence of episode, we can train our network to match long-short utterance pair well rather than conventional (also referred as vanilla) training, where same length of utterance is optimized at once. Yet, a crucial problem here is that the query samples could not be discriminative against whole classes in training set. Therefore, we further classify every sample in episode over whole training classes (also referred as global classification). In doing so, embedding of short utterance can be discriminative against other classes and matched to its own long utterance at the same time. (See Figure 1)

Also, SR system should be robust to speech duration to cope with practical situation, since same person can speak at different speed and it varies from person to person. To deal with this problem, we meta-learn the model by simulating the real situation. Specifically, query utterance has variable length which is smaller than support one as like enroll and test pair in practice. This allows the model to consider various scenarios during meta-learning and thus allows to obtain more robust model to duration for test utterance. Also, consistent framework between training and testing makes the model be able to verify and classify unseen speaker well. (See Figure 2)

Our proposed learning scheme is based on ResNet34 [4], which is widely used in SR. To verify efficiency of our proposed model, we just use aggregation as temporal average pooling (TAP) and non-margin metric loss. Also, we use input feature as 40-dimensional log-Mel filterbank to reduce time complexity, since in the realistic setting the execution time should be short. We experiment on realistic setting such as short utterance SV and unseen SI including conventional experiment setting (full utterance SV). We use VoxCeleb datasets [5][6] to directly compare with other models. Our model obtains state-of-the-art results on short utterance and we show results of our model in various test data and settings for ease comparison and reproduction.

Our main contributions are as follows:

• We propose a novel meta-learning method for short utterance speaker recognition, in which each episode is composed of support and query pair of imbalance utterance length.

• We propose a training procedure that combines meta-learning and global classification to get well-matched and discriminated embedding.

• We validate our model on VoxCeleb datasets for various realistic setting including speaker verification with short duration and unseen speaker identification and achieve state-of-the-art results.

2. Related Work

DNN based speaker embedding: Recently, speaker recognition (SR) has achieved impressive performance through the DNN based methods [7][8][9][10]. The key component of DNN based system is feature extractor, aggregation of temporal features and optimization. First, many SR systems use 1D or 2D convolutional neural network and recurrent neural network as feature extractor. These extractors made it possible to extract the time and frequency properties of the speaker features (MFCC, mel-filter bank). Extracted frame-level features are summarized as fixed length vector by aggregation methods. There has been many works to capture intrinsic speaker information such as attentive statistic pooling (ASP) [11], self attentive pooling (SAP)
In this work, we tackle practical setting for unseen speaker recognition, where the length of test utterance is shorter than enrollment utterance. Therefore, a suitable model for this situation should not only have a ability to make long utterance and short utterance match well but classify unseen speakers well. We introduce meta-learning scheme, where support set and query set is consist of long and short utterance respectively. We also classify

support and query set over whole training classes to make it discriminative, while imbalance pair is matched.

3.1. Problem Definition

In the $N$-way $K$-shot classification, we first sample $N$ classes randomly from the entire set of classes, and then sample $K$ and $M$ examples from each class for the support set and query set, respectively. We define episode sampling distribution as $p(\tau)$. As a result, we have a support set $S = \{(x_1, y_1), (x_2, y_2), \ldots, (x_{N\times K}, y_{N\times K})\}$ and query set $Q = \{(\tilde{x}_1, \tilde{y}_1), (\tilde{x}_2, \tilde{y}_2), \ldots, (\tilde{x}_{N\times M}, \tilde{y}_{N\times M})\}$, where $y, \tilde{y} \in \{1, \ldots, N\}$ are the class labels.

The goal of classification in episode is to correctly classify query examples in $Q$ given the support set $S$. Since $S$ includes only a few examples for each class, conventional learning algorithms will mostly fail due to overfitting (e.g. consider 1-shot classification). Thus, most existing approaches tackle this problem by meta-learning over a task distribution $p(\tau)$, such that the later tasks can benefit from the knowledge obtained over the previous training episodes.

One of the most popular and successful approaches for few-shot classification is the metric-based approach. We aim to learn an embedding function $f_{\theta}(\cdot) : \mathbb{R}^l \rightarrow \mathbb{R}^l$ that maps an input $x$ to an $l$-dimensional metric space. Support set and query set are then mapped into this space, such that we can measure the distance between class prototypes and query embeddings. In this paper, we use cosine similarity as distance metric.

3.2. Meta-Learning for imbalance length pair

Despite of large improvement on speaker recognition, speaker recognition with short duration remains very challenging. Our proposed learning paradigm deals with this problem in realistic perspect. As proved in [29], in conventional training setting, mismatch of length between train and test speech can degrade performance for short utterance. In other words, as shown in [24], model trained with short segment performs better with short test utterance than model trained with relatively long speech, but with relatively poor performance with long speech. This trade-off is very fatal to realistic settings, leading to not discriminative embedding of enrollment or test utterance.

If so, how can we train robust models for duration of utterance? To tackle this problem, we meta-learn the model with episode, where support set and query set is constructed by imbalanced length pair. In practical setting, once we enroll long
utterance, it is fixed and then test utterance with variable and short length is entered into system. To simulate this situation in training phase, we set the support set longer than query utterance. Contrariwise, query set is consist of variable length feature, which is shorter than support utterance.

As doing in [19], we make the prototype by average of support set and let the query examples close to be prototype. First, we define $\mathcal{S}_c$ as the set of support examples in class $c$ and then compute the prototype of each class $c = 1, \ldots, N$ in episode:

$$P_c = \frac{1}{|\mathcal{S}_c|} \sum_{x \in \mathcal{S}_c} f(x)$$

(1)

Then, we compute distance between each query and prototype. In this work, we use cosine similarity as distance metric:

$$d(f(x), P_c) = \frac{f(x) \cdot P_c}{\|P_c\|_2} = \|f(x)\|_2 \cdot \cos(\theta, c)$$

(2)

where it can be seen as cosine similarity with an input-wise length scale. So, we can predict for each class $c$ as following:

$$p(y|x; \theta) = \frac{\exp(d(f(x), P_c))}{\sum_{c} \exp(d(f(x), P_c))}$$

(3)

where $d$ is distance metric described in Eq. (2). Note that global classification is conducted on both support and query samples. Finally, our learning objective combines the episode loss in Eq. (7) with the global loss in Eq. (7).

$$L(\theta, \omega) = \mathbb{E}_{\mathcal{P}(x)} \left[ L^g_{\theta}(\theta) + \lambda L^v_{\theta}(\theta, \omega) \right]$$

(8)

Table 1: Verification performance on full utterance. A: A-softmax; SM: Softmax; NS: Normalized softmax; G: Global classification; M: Meta-learning; NR: Not reported; *: With data augmentation.

| Model | (Aggregation-Loss) | M | Feature | Train dataset | C_\text{det} / EER% |
|-------|--------------------|---|---------|---------------|-------------------|
| i-vectorsPLDA [5] | × | NR | V oxCeleb1(D) | 0.73 / 8.8 |
| VGG-M (TAP+C) [10] | × | Spec-512 | V oxCeleb1(D) | 0.71 / 7.8 |
| ResNet34 (TAP+A) [10] | × | MFBC-64 | V oxCeleb1(D) | 0.622 / 4.40 |
| ResNet34 (SPE+A) [13] | × | MFBC-64 | V oxCeleb1(D) | 0.402 / 4.03 |
| TDNN (ASPP+SM) [11] | × | MFBC-40 | V oxCeleb1(D) | 0.406 / 3.85 |
| ResNet34 (TAP+NS) | / | MFBC-40 | V oxCeleb1(D) | 0.418 / 3.81 |
| UtterIdNet (1DV+SM) [11] | × | Spec-257 | V oxCeleb2(D) | 0.624 / 4.26 |
| Thin ResNet34 [4] | × | Spec-257 | V oxCeleb2(D) | NR / 3.22 |
| (GhostVlad+SM) | × | Spec-257 | V oxCeleb2(D) | 0.245 / 6.61 |
| ResNet34 (SPE+A) [13] | × | MFBC-64 | V oxCeleb2(D) | 0.245 / 6.61 |
| ResNet34 (TAP+NS) | / | MFBC-40 | V oxCeleb2(D) | 0.234 / 2.08 |

where $\lambda$ is balance factor of loss and we simply set the $\lambda$ to 1. We average task distribution $p(\tau)$ via Monte-Carlo (MC) approximation with a single sample during training. This combined objective allows model to match imbalance length pair, while this pair is classified over whole training classes together.

4. Experiments

4.1. Dataset

We experiment our method on various setting with VoxCeleb datasets. VoxCeleb1 [5] and VoxCeleb2 [6] are large scale text-independent speaker recognition datasets. Each of them consists of 1251 and 5994 speakers respectively. Speakers in these two datasets do not overlap. Verification results are presented with equal error rate(EER) and the minimum detection cost function(minDCF or $C_{\text{min}}$) at $P_{\text{target}} = 0.01$. Verification trials are scored using cosine similarity. For the unseen speaker identification, average accuracy over 1000 randomly generated episodes is reported with 95% confidence intervals.

4.2. Experiment setting

We use input feature as 40-dimensional log Mel-iterbank(MFB) features with a frame-length of 25 ms, which are overlapping adjacent frames by 15ms. Inputs are mean-normalized along time-axis without any voice activity detection(VAD) and data augmentation. In training episode, we use 1-shot 100-way and the number of query examples for each class is set to 2. For the memory efficiency, we set length of support set to 2 seconds and the length of the query to between half and full of the support length. For the vanilla training, we use fixed length speech at 2 seconds. Frame-level feature extractor is ResNet34 with 32-64-128-256 channels for each residual stage. Extracted feature are aggregated with temporal average pooling(TAP) and it passes through the fully-connected layer to be 256-dimensional embedding. We use SGD optimizer with the Nesterov momentum of 0.9 and set the weight decay to 0.0001. We set initial learning rate to 0.1 and decay it by a factor of 10 until convergence. Every experiment is done on a single NVIDIA 2080Ti GPU.

4.3. Speaker verification for full utterance

We first examine the result of full duration SV to analyze the advantage of using our training scheme. Every results in Table 1 are evaluated on VoxCeleb1 [5] original test set. For fair comparison, we report baselines without VAD and data augmentation except x-vector [9] based model [11]. For the VoxCeleb1, our proposed model outperforms previous state-of-the-arts models. For the same backbone(i.e. ResNet34), our model achieves su-
Table 2: Verification performance on short utterance. G: Global classification; M: Meta-learning; Spec: Spectrogram; D: Development set; T: Test set; *: With data augmentation.

| Model(Aggregation+Loss) | G | M | Feature | Train dataset | Test dataset |
|-------------------------|---|---|---------|---------------|--------------|
| ResNet34(TAP+NS)        | √ | × | MFB-40  | Vox1(D)       | 9.31         |
| ResNet34(TD+NS)         | [2]| × | MFB-40  | Vox1(D)       | 9.12         |
| ResNet34(TAP+NS)        | × | √ | MFB-40  | Vox1(D)       | 8.44         |
| ResNet34(TAP+NS)        | √ | × | MFB-40  | Vox1(D)       | 5.35         |
| Thin ResNet34(GhostVlad+SM) | [2]| × | Spec-23 | Vox2(D)       | 12.71        |
| ResNet34(SAP+AM)        | [2]| × | MFB-80  | Vox2(D)+T     | 9.91         |
| ResNet34(TAP+NS)        | √ | × | MFB-40  | Vox2(D)+T     | 5.31         |

Table 3: Ablation study on length pair of training utterance. All models are meta-learned without global classification. VoxCeleb1 development set and test set are used for training and testing respectively.

| Support length | Query length | EER% 1s | EER% 2s | EER% 5s | EER% full |
|----------------|--------------|---------|---------|---------|----------|
| 1s             | 1s           | 7.32    | 6.66    | 5.05    | 4.84     |
| 2s             | 1s           | 8.81    | 6.56    | 5.36    | 4.94     |
| 2s             | 1s-2s        | 8.44    | 6.33    | 4.81    | 4.52     |

Table 4: Accuracy(%) of unseen speaker identification.

| Query length | Training method | 5-way | 20-way | 50-way | 100-way |
|--------------|-----------------|-------|--------|--------|---------|
|              | Vanilla         | 94.77 | 85.03 | 73.72  | 57.93   |
|              | Ours            | 96.40 | 88.92 | 82.11  | 75.92   |
| 1s           | Vanilla         | 97.18 | 89.63 | 81.45  | 77.72   |
|              | Ours            | 98.38 | 94.91 | 90.90  | 86.49   |

4.4. Speaker verification for short utterance

We first describe the test setting, then compare other previous state-of-the-arts models for short utterance. We test our model on two datasets. First is original VoxCeleb1 test trial which is the same one used to evaluate full utterance. Second is VoxCeleb1 full dataset(1251 speakers in total). Enrollment utterance is used for full duration, but test utterance is randomly cropped by 1, 2 and 5 seconds. If the test utterance is shorter than required, we duplicate sample using segment in its own.

To prove efficiency of our model, we perform an ablation study with VoxCeleb1. We observe that Time Distributed Voting(TDV) [2] which is proposed to aim at short segment outperforms temporal average pooling with slight margin. But, the result of third row shows that model only trained with meta-learning outperforms TDV and conventionally trained model(See first row). Further, our proposed model that combine meta-learning with global classification gets the best performance against other baselines trained on VoxCeleb1 with large margin.

For the comparison with other previous state-of-the-arts models [2][3][24], we trained the model with VoxCeleb2 dataset and tested on VoxCeleb1 full dataset. We use same trial as described in [24]. For every speaker, trial is randomly generated for 100 positive pairs and 100 negative pairs. Bottom rows in Table 2 show that our model outperforms other baselines with significantly large margin for 1-2 seconds. Since our model doesn’t use any other aggregation technique and margin-based optimization, we can say that its impressive improvement is only due to our combined learning scheme. Furthermore, our model uses only 40-dimensional feature but the other baselines use more than twice the dimensions. As proven in [24], it means that the performance gap can be bigger if we use higher dimensional inputs. For the comparison with [2], since UtterIdNet is not publicly available, we compared it using TDV instead.

Our performance gain is due to two reasons. First, we compose training episode with imbalance length pair, where utterance length of query is variable and shorter than support set. In Table 2, we can observe that variable short every setting outperforms both equal length pair and fixed long-short pair. Note that [26][27] are a kind of equal length pair. In our proposed setting, model comes across various length pair setting for each episode, and then is meta-learned to be good at matching imbalance length pair and robust to speech duration. Secondly, to make more discriminative embedding, we classify both support and query samples against whole training classes. Unlike the conventional method which classify the same length for each batch, our combined scheme classifier different length at once. It results in reduction of variance caused by duration and enlarges inter-class cluster. With combined these two components, our proposed model shows state-of-the-arts performance in short utterance, resulting good performance in full utterance.

4.5. Unseen speaker identification

Now, we evaluate the performance of our model on unseen SI. To analyze our model, we trained the model on VoxCeleb2 dataset and tested on whole VoxCeleb1 dataset. For similar setting with verification, we enroll with one utterance and the enrollment utterance was equally set to 5 seconds to be fairly classified. Therefore, We randomly sample N-speakers from VoxCeleb1 dataset, and then sample 1 and 5 samples from each speakers for enrollment and test utterance, respectively. For test utterance shorter than required, we handled it as in 4.4. As shown in Table 4, our proposed method outperforms vanilla training in every setting. The performance gap increases as the number of classification classes grows. Generally, the performance of identification decreases as the number of speaker is larger and as the length of utterance is shorter.

5. Conclusion

We proposed a novel meta-learning scheme for short duration speaker recognition. In order to simulate actual setting in training, we propose episode composition in which support and query set have imbalance length. Our meta-learning scheme is combined with global classification, resulting well-discriminated embedding space. With the VoxCeleb datasets, we validate our model on various settings and obtain state-of-the-art performance on short utterance speaker verification.

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References

[1] Z. Gao, Y. Song, I. V. McLoughlin, W. Guo, and L.-R. Dai, “An improved deep embedding learning method for short duration speaker verification,” in *Interspeech*, 2018.

[2] A. Hajavi and A. Etemad, “A deep neural network for short-segment speaker recognition,” in *Interspeech*, 2019.

[3] W. Xie, A. Nagrani, J. S. Chung, and A. Zisserman, “Utterance-level aggregation for speaker recognition in the wild,” in *ICASSP 2019-2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE, 2019, pp. 5791–5795.

[4] K. He, X. Zhang, S. Ren, and J. Sun, “Deep residual learning for image recognition,” in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2016, pp. 770–778.

[5] A. Nagrani, J. S. Chung, and A. Zisserman, “Voxceleb: a large-scale speaker identification dataset,” *arXiv preprint arXiv:1706.08612*, 2017.

[6] J. S. Chung, A. Nagrani, and A. Zisserman, “Voxceleb2: Deep speaker recognition,” *arXiv preprint arXiv:1806.05622*, 2018.

[7] E. Variani, X. Lei, E. McDermott, I. L. Moreno, and J. Gonzalez-Dominguez, “Deep neural networks for small footprint text-dependent speaker verification,” in *2014 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE, 2014, pp. 4052–4056.

[8] C. Li, X. Ma, B. Jiang, X. Li, X. Zhang, X. Liu, Y. Cao, A. Kannan, and Z. Zhu, “Deep speaker: an end-to-end neural speaker embedding system,” *arXiv preprint arXiv:1705.02304*, 2017.

[9] D. Snyder, D. Garcia-Romero, G. Sell, D. Povey, and S. Khudanpur, “X-vectors: Robust dnn embeddings for speaker recognition,” in *2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE, 2018, pp. 5329–5333.

[10] C. Zhang, K. Koishida, and J. H. Hansen, “Text-independent speaker verification based on triplet convolutional neural network embeddings,” *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, vol. 26, no. 9, pp. 1633–1644, 2018.

[11] K. Okabe, T. Koshinaka, and K. Shinoda, “Attentive statistics pooling for deep speaker embedding,” *arXiv preprint arXiv:1803.10963*, 2018.

[12] W. Cai, J. Chen, and M. Li, “Exploring the encoding layer and loss function in end-to-end speaker and language recognition systems,” *arXiv preprint arXiv:1804.05160*, 2018.

[13] Y. Jung, Y. Kim, H. Lim, Y. Choi, and H. Kim, “Spatial pyramid encoding with convex length normalization for text-independent speaker verification,” *arXiv preprint arXiv:1906.08333*, 2019.

[14] W. Liu, Y. Wen, Z. Yu, M. Li, B. Raj, and L. Song, “Sphereface: Deep hypersphere embedding for face recognition,” in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2017, pp. 212–220.

[15] F. Wang, J. Cheng, W. Liu, and H. Liu, “Additive margin softmax for face verification,” *IEEE Signal Processing Letters*, vol. 25, no. 7, pp. 926–930, 2018.

[16] J. Deng, J. Guo, N. Xue, and S. Zafeiriou, “Arcface: Additive angular margin loss for deep face recognition,” in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2019, pp. 4690–4699.

[17] S. M. Kye, H. B. Lee, H. Kim, and S. J. Hwang, “Transductive few-shot learning with meta-learning confidence,” *arXiv preprint arXiv:2002.12017*, 2020.

[18] O. Vinyals, C. Blundell, T. Lillicrap, D. Wierstra et al., “Matching networks for one shot learning,” in *Advances in neural information processing systems*, 2016, pp. 3630–3638.

[19] J. Snell, K. Swersky, and R. Zemel, “Prototypical networks for few-shot learning,” in *Advances in neural information processing systems*, 2017, pp. 4077–4087.

[20] Y. Liu, J. Lee, M. Park, S. Kim, E. Yang, S. J. Hwang, and Y. Yang, “Learning to propagate labels: Transductive propagation network for few-shot learning,” *arXiv preprint arXiv:1805.10002*, 2018.

[21] J.-w. Jung, H.-s. Heo, H.-j. Shim, and H.-J. Yu, “Short utterance compensation in speaker verification via cosine-based teacher-student learning of speaker embeddings,” in *2019 IEEE Automatic Speech Recognition and Understanding Workshop (ASRU)*. IEEE, 2019, pp. 335–341.

[22] J. Zhang, N. Inoue, and K. Shinoda, “I-vector transformation using conditional generative adversarial networks for short utterance speaker verification,” *arXiv preprint arXiv:1804.00290*, 2018.

[23] Z. Huang, S. Wang, and K. Yu, “Angular softmax for short-duration text-independent speaker verification,” in *Interspeech*, 2018, pp. 3623–3627.

[24] A. Gusev, V. Volokhov, T. Andzhukhaev, S. Novoselov, G. Lavrentyeva, M. Volkova, A. Gazizzullina, A. Shulipa, A. Gorlanov, A. Avdeeva et al., “Deep speaker embeddings for far-field speaker recognition on short utterances,” *arXiv preprint arXiv:2002.06033*, 2020.

[25] A. Kanagasundaram, S. Sridharan, S. Ganapathy, P. Singh, and C. B. Fookes, “A study of x-vector based speaker recognition on short utterances,” in *Interspeech*, 2019.

[26] J. Wang, K.-C. Wang, M. T. Law, F. Rudzicz, and M. Brudno, “Centroid-based deep metric learning for speaker recognition,” in *ICASSP 2019-2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE, 2019, pp. 3652–3656.

[27] P. Anand, A. K. Singh, S. Srivastava, and B. Lall, “Few shot speaker recognition using deep neural networks,” *arXiv preprint arXiv:1904.08775*, 2019.