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# A Hybrid of Deep Audio Feature and i-vector for Artist Recognition

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## Abstract

Artist recognition is a task of modeling the artist’s musical style. This problem is challenging because there is no clear standard. We propose a hybrid method of the generative model i-vector and the discriminative model deep convolutional neural network. We show that this approach achieves state-of-the-art performance by complementing each other. In addition, we briefly explain the advantages and disadvantages of each approach.

## 1. Introduction

The musical style of artist is an important feature in several music information retrieval tasks such as recommending similar artists. However, since there is no clear standard for this, early approaches proposed to extract and combine various hand-crafted audio features such as timbre, harmonic contents, etc. (Bergstra et al., 2006; Ellis, 2007). Recent approaches focused on modeling artist by leveraging the i-vector speaker and artist recognition systems (Eghbal-Zadeh et al., 2015). In this paper, we adopt deep audio feature extracted from deep convolutional neural network (DCNN) combining with i-vector to alleviate the limitation of compact frame-level representation by capturing higher-level artist feature.

**i-vector:** The i-vector is the state-of-the-art algorithm in a speaker verification (Dehak et al., 2011) and also showed good performance on artist classification task (Eghbal-Zadeh et al., 2015). We implemented i-vector using 20-dim Mel-Frequency Cepstrum Coefficients with Gaussian mixture model of size 256. We use probabilistic linear discriminant analysis (PLDA) to compute the i-vector score (Kenny, 2010).

**DCNN:** Representation learning has been actively explored in recent years as an alternative to feature engineering (Bengio et al., 2013). We construct the DCNN with five con-

volutional layer and one fully-connected layer to classify the artists using 3-second mel-spectrogram with 128 bins as input. We use the DCNN as a feature extractor and the last hidden layer (256-dim vector) as a deep audio feature. PLDA is also applied as a scoring method.

The results show that i-vector and DCNN capture the characteristics of each artist differently. We also found that the two methods above are complementary to each other by showing that a hybrid approach performs better.

## 2. Experimental Setup

We conducted artist recognition on Million Song Dataset (MSD) (Bertin-Mahieux et al., 2011) by artist verification and artist identification. We filtered out 20 songs for each artist which are randomly selected including various albums to prevent recording environment effects. Apart from the training data, we use 500 unseen artists for the evaluation. For evaluation, 15 songs are used to enroll each artist model and remaining 5 songs are used for testing. We aggregate the 15 track vectors to make artist model by averaging.

**Artist verification:** We compute the distance between the claimed artist model and the test feature vector. We evaluate the verification task in terms of equal error rate (EER), where both acceptance and rejection error rates are equal.

**Artist identification:** There are 500 artist models and the task is choosing one of them by computing distance between the test feature vector and all artist models. We evaluate the identification task in terms of classification accuracy, which is calculated by dividing the number of correct results by the total number of test cases.

## 3. Results

### 3.1. The Number of Training Artists

We used increasing number of artists equally in training i-vector and DCNN to investigate how the number of artists affects the performance. Figure 1 shows the experimental results of verification and identification, respectively. In both cases, the performances of DCNN are continuously improved as the training artists increase, while i-vector converges. This might be related to our experimental setting where 500 artist identity models are used in evaluation. That is, in order to discriminate a large number of artists, the

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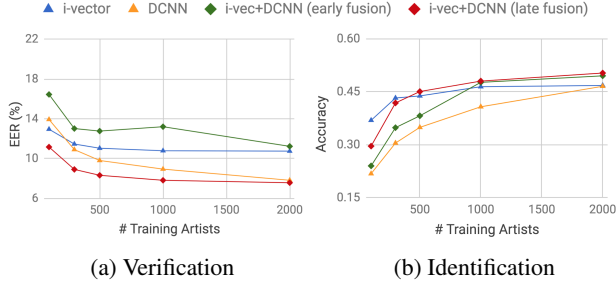


Figure 1. Results of the artist recognition tasks.

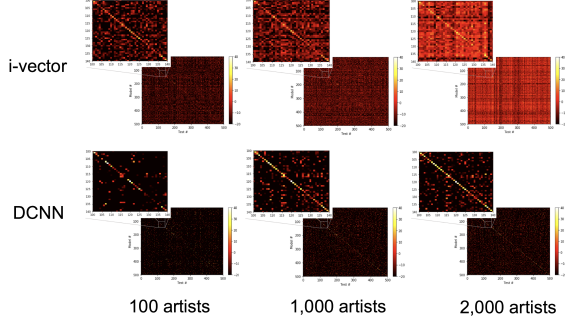


Figure 2. Comparison of the score matrices of i-vector and DCNN with different number of training artists.

supervised feature learning with DCNN also requires an equivalent or larger number of artists, accordingly. On the other hand, i-vector, which is based on unsupervised learning, is less sensitive to the number of training artists.

### 3.2. Confusion Matrix

These characteristics are also found in Figure 2, which shows the score matrices with increasing the number of training artists. Each element means the similarity  $S(x_i, x_j)$  where  $x_i$  denotes the feature vector of  $i$ th artist. In this figure, we can see that, as the training artists increase, the empty portion in the middle of the diagonal line in DCNN is gradually filled. However, still, some artists' identity models are not formed well. On the other hand, i-vector can form each artist model even though the number of training artists is small. However, as the number of the training artists increases, the similarity with other artists as well as their own models increases, which makes the performance of i-vector converges. These characteristics can explain the reason why i-vector outperforms DCNN in identification task and when the number of training artists is small, whereas DCNN outperforms in verification task in Figure 1.

### 3.3. Singer Recognition

Because singing voice is one of the main concerns of musical pieces, and most people use the singing voice as the primary cue for recognizing a song, we also perform singer recognition to distinguish music more focusing on singing

	Verification (EER)				Identification (Accuracy)			
	i-vec	DCNN	Early	Late	i-vec	DCNN	Early	Late
Artist	10.785	8.938	13.200	7.813	0.464	0.408	0.477	0.480
Singer	8.257	7.611	10.179	3.241	0.560	0.435	0.430	0.760

Table 1. The comparison of the results between artist and singer. 1,000 artists and singers are used for training in this experiment, respectively.

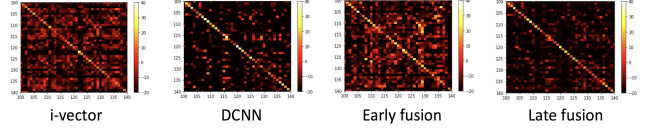


Figure 3. Comparison of the score matrices of i-vector, DCNN, early fusion and late fusion when the number of training singers is 1,000.

voice. We selected *singers* using a CNN-based singing voice detector (Schlüter & Grill, 2015) by regarding the artist who has more than 20 audio clips with 70% vocal confidence as a singer. Table 1 shows the comparison results between artist and singer recognition. Compared to the artist recognition and DCNN, i-vector results are greatly improved in singer recognition. This indicates that i-vector distinguishes the human voice more clearly than music audio, and it may be related that i-vector was designed for speaker recognition.

### 3.4. Hybrid Methods

We also compare two hybrid methods of combining DCNN and i-vector. One is early fusion that concatenates deep audio feature and i-vector into a single feature vector before scoring, and the other is late fusion that uses the average evaluation score from both features. In Figure 1, late fusion achieves best results for all cases, whereas early fusion is generally worse than either i-vector or DCNN. In addition, the late fusion results are significantly improved in singer recognition in Table 1. From Figure 3, we can explain the reason as early fusion seems to suppress the feature of each model by causing confusion to distinguish, while late fusion seems to take the advantages of each model and offset the disadvantages by complementing each other. A similar result can be found in audio scene classification (Eghbal-Zadeh et al., 2016).

## 4. Conclusions

In this paper, we conducted artist recognition by verification and identification. From the results, we showed that the late fusion of deep audio feature and i-vector achieves best performance by complementing each other. We also explained the advantages and disadvantages of each approach. For future work, we will develop the aggregating method and apply the proposed method to recommend similar artists.

## References

- Bengio, Yoshua, Courville, Aaron, and Vincent, Pascal. Representation learning: A review and new perspectives. *IEEE Trans. Pattern Anal. Mach. Intell.*, 35(8), August 2013.
- Bergstra, James, Casagrande, Norman, Erhan, Dumitru, Eck, Douglas, and Kégl, Balázs. Aggregate features and adaboost for music classification. *Machine Learning*, 65: 473–484, December 2006.
- Bertin-Mahieux, Thierry, Ellis, Daniel PW, Whitman, Brian, and Lamere, Paul. The million song dataset. In *Ismir*, volume 2, pp. 10, 2011.
- Dehak, N., Kenny, P. J., Dehak, R., Dumouchel, P., and Ouellet, P. Front-end factor analysis for speaker verification. *IEEE Transactions on Audio, Speech, and Language Processing*, pp. 788–798, 2011.
- Eghbal-Zadeh, Hamid, Lehner, Bernhard, Schedl, Markus, and Widmer, Gerhard. I-vectors for timbre-based music similarity and music artist classification. In *Proceedings of the International Society for Music Information Retrieval Conference (ISMIR)*, pp. 554–560, 2015.
- Eghbal-Zadeh, Hamid, Lehner, Bernhard, Dorfer, Matthias, and Widmer, Gerhard. CP-JKU submissions for dcase-2016: A hybrid approach using binaural i-vectors and deep convolutional neural networks. *IEEE AASP Challenge on Detection and Classification of Acoustic Scenes and Events (DCASE)*, 2016.
- Ellis, Daniel PW. Classifying music audio with timbral and chroma features. In *ISMIR 2007: Proceedings of the 8th International Conference on Music Information Retrieval: September 23-27, 2007, Vienna, Austria*, pp. 339–340. Austrian Computer Society, 2007.
- Kenny, Patrick. Bayesian speaker verification with heavy-tailed priors. In *Odyssey*, pp. 14, 2010.
- Schlüter, Jan and Grill, Thomas. Exploring data augmentation for improved singing voice detection with neural networks. In *Proceedings of the International Society for Music Information Retrieval Conference (ISMIR)*, pp. 121–126, 2015.