ABSTRACT

Pre-training has been a popular learning paradigm in deep learning era, especially in annotation-insufficient scenario. Better ImageNet pre-trained models have been demonstrated, from the perspective of architecture, by previous research to have better transferability to downstream tasks[1]. However, in this paper, we found that during the same pre-training process, models at middle epochs, which is inadequately pre-trained, can outperform fully trained models when used as feature extractors (FE), while the fine-tuning (FT) performance still grows with the source performance. This reveals that there is not a solid positive correlation between top-1 accuracy on ImageNet and the transferring result on target data. Based on the contradictory phenomenon between FE and FT that better feature extractor fails to be fine-tuned better accordingly, we conduct comprehensive analyses on features before softmax layer to provide insightful explanations. Our discoveries suggest that, during pre-training, models tend to first learn spectral components corresponding to large singular values and the residual components contribute more when fine-tuning.

Keywords Transfer Learning · Inadequately Pre-trained Models

1 Introduction

Deep learning have obtained tremendous success in modern computer vision with help of strong supervision of well-labeled datasets, such as ImageNet[2]. However, data annotation is notoriously labor-extensive and time-consuming, especially in some specific domain where expertized knowledge is required. In such occasion, transfer learning is of great interest for practioners to train deep models with a small labeled dataset. Fortunately, researchers find that, when training on large scale datasets, middle features of DNNs exhibit remarkable transferability to various downstream tasks [3,4]. This facilitates popular deep transfer learning paradigms of fine-tuning a pre-trained model (FT) or simply employing the pre-trained model as a feature extractor (FE). With relatively sufficient labeled examples, fine-tuning the whole network usually achieves higher performance. Despite this, FE is still important when training resources are limited, or an end-to-end training is not feasible. For example, some applications combine DNN features and other handcrafted features to obtain both accurate and explainable shallow classifiers [5][6][7].
Figure 1: Toy experiment of transfer learning from a ResNet18 [15] model pre-trained on CIFAR10 [16] to a subset of MNIST [17]. FE means viewing the pre-trained model as a feature extractor, and FT means fine-tuning the whole model. It can be seen from the figure that the 5th-epoch model brings the best FE performance, which suggests that further pre-training on the source task would harm the feature quality for the target task. When fine-tuning the whole model, more adequately pre-training tends to deliver higher transfer learning performance.

Despite the ubiquitous utilization of pre-trained models, how they benefit transfer learning has been still poorly understood. Few empirical studies investigating this problem have been published. [1] systematically investigates whether models perform better on the source task, e.g. ImageNet, necessarily transfer better on downstream tasks. They confirm this hypothesis for both FE and FT, over deep architectures with different capacities. However, recent works in the domain of adversarial training discover that an adversarially pre-trained model, though performs worse on ImageNet due to additional adversarial regularization, transfers better than its natural (following the denotation in [8], which means pre-training without adversarial methods) counterpart (with the same architecture) [9, 8]. Actually, these discoveries are opposite to [1] to some extent that, worse source models may have better transferability.

Our work investigates how pre-training influences transfer learning from a different perspective. Specifically, we focus on the trajectory of the pre-training process. Our study is inspired by recent investigations about the learning order of DNNs. Several works [10, 11, 12, 13] discover that, DNNs tend to first learn simple and shallow features, e.g. colors and textures. These shallow features are regarded as more general and transferable across different data domains [3]. From a perspective of frequency domain, they belong to low-frequency spectrums. On the other hand, some empirical works reveal that, high-frequency features obtained by the pre-trained model are likely to cause negative transfer [14].

Above observations motivate an intuitive question that, does the fully pre-trained model definitely outperforms inadequately pre-trained ones when transferring to target tasks (according to claims in [1]), or there exists a middle pre-training checkpoint that transfers best? To the best of our knowledge, there has been no research towards validating the difference of transferability between models in a same pre-training process.

To investigate this question, we run a toy experiment using CIFAR10 as the source dataset and a subset of MNIST (we randomly choose 100 data points for each digit from the official training split, resulting in a 1000-sample training set) as the target. Briefly, we train a ResNet-18 [15] on CIFAR10 for 200 epochs, and choose a set of checkpoints to run transfer learning in two different settings: one is to view the pre-trained model as a feature extractor and only retrain a softmax classifier (FE), the other is to fine-tune the whole model (FT). The maximum epoch for transfer is 100. As shown in Figure 1, the best performance of FE comes from the 5th-epoch model, while the FT performance is higher on later checkpoints.
Two counterintuitive facts can be observed from our results. One is that, a pre-trained model with higher accuracy on the source task is not necessarily better on the target task, especially when used as a feature extractor (FE). Among checkpoints on the pre-training trajectory, there is no positive correlation between the source and target accuracy. The other observation shows inconsistent behaviors between FE and FT, implying that a good starting point (FE) does not guarantee a good final result (FT). In order to explain the observed phenomena, we investigate the spectral components of deep features before the FC layer (in Section 4.4), and point out that different part of components contribute diversely for different pre-trained checkpoints within a same pre-training process.

In this paper, we conduct extensive transfer learning experiments from ImageNet to 9 representative datasets. The results suggest that, when retraining a new classifier on the top of the features extracted from pre-trained models, inadequately pre-trained ImageNet models have obviously better performance than standard 90-epoch pre-trained one does, but the performance still highly correlates with source performance when fine-tuning. Further, we conduct insightful analysis to explain such difference from the perspective of spectral components of the extracted features, and we find that there are specific components corresponding to pre-trained models different pre-training stages. Our main contributions are as follows:

- Our work is the first to investigate how different checkpoints in a same pre-training process perform on transfer learning tasks. This contributes to broader and deeper understandings about transferability of DNNs.
- We discover that in the same pre-training process, an inadequately pre-trained model tends to transfer better than its fully pre-trained counterpart, especially when using the pre-trained model as a frozen feature extractor.
- We discover that FT prefers later pre-training checkpoints than FE. Our analyses based on spectrum decomposition indicate that the learning order of different feature components leads to different pre-trained model preferences between FE and FT.
- Our observations also point out the risk of utilizing transferability assessment approaches as a general tool to select pre-trained models. We evaluate the state-of-the-art algorithm LogME [18], which is dependent on frozen pre-trained models. Aiming to select the best pre-trained model among different checkpoints, scores obtained by these algorithms show bad correlations with the actual fine-tuning performance.

## 2 Related Work

Pre-training on large datasets, such as ImageNet [2], has long been a common method for transfer learning in various kinds of downstream tasks. Due to the huge effort brought by data annotation, researchers have reached a consensus that supervised or unsupervised pre-training as a parameter initialization or even an important medium for representation learning on existed large datasets is beneficial [19, 20] for general downstream tasks [21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31] or specific ones [32, 33, 34]. Zeiler et al. [3] have found that retraining a softmax classifier on top of fixed pre-trained feature would benefit classification on target data by a large margin compared with training from scratch. In recent years, designing different kinds of pretext tasks (e.g., jigsaw puzzle [21], rotation angle prediction [35], temporal order prediction [22]) as a self-supervised pre-training methods became a popular trend in this community. Later on, contrastive learning [24, 25, 26, 27] has also been demonstrated as a better self-supervised pre-training approach. Beyond vision domain, large-scale unsupervised pre-training in speech and natural language [36, 37, 38, 39, 40] is appealing as well. Furthermore, learning universal representation and capturing cross-modal correspondence by pre-training in a multimodality setting [41, 42] plays an important role in the development of artificial general intelligence [43].

With such powerful impact on deep learning, in computer vision community, researchers have also been trying to understand the mechanism behind the success of pre-training, especially the ImageNet case, since ImageNet indeed has strong transferring power even to different data domain (e.g., in geoscience [44] and biomedical science [45]). Erhan et al. [46, 47] experimentally validated the role of unsupervised pre-training as a regularizer for the following supervised learning. Huh et al. [47], via designing thorough experiments, answer a series of questions about the performance difference of transferring brought by different aspects (e.g., number of training samples, number of training classes, fine-grained or coarse-grained pre-training, etc.) of ImageNet. Using proper normalization method and extending the training time, He et al. [48] challenge this well-established paradigm and argue that it is possible to obtain better performance on target data from random initialization in detection and segmentation tasks. Following this work, Zoph et al. [49] further point out that self-training, with stronger data augmentation, can also lead to better transferring performance than pre-training. Nonetheless, pre-training is also viewed as a helpful training fashion for downstream tasks from different perspectives. Hendrycks et al. [50] have discovered that, in task-specific methods (e.g., label corruption, class imbalance, adversarial examples, etc.), pre-training enhances model robustness and brings consistent improvement that regular approaches.

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Aiming to investigate what kinds of pre-training models could bring better transferring performance, Kornblith et al.\[1\] conduct extensive experiments on 16 different network architectures and suggest that models with higher top-1 accuracy on ImageNet could learn better transferable representations for target tasks. From the perspective of adversarial training, Utrera et al.\[8\] found that adversarially-trained models, though perform poorer on source data, actually have stronger transferability than natural models. And they further claimed that adversarially-trained models can learn more human-identifiable semantic information. Later, focusing more on model architecture, Salman et al.\[9\] drew a same conclusion, which further consolidate this viewpoint. In this work, we further investigate the relationship between top-1 accuracy on ImageNet and the performance in target tasks, and found that some suboptimal models during pre-training transfer better when viewed as feature extractor, which is a analogous phenomenon with early-stopping\[51, 52\] in supervised learning that higher accuracy on training set does not mean higher test performance.

In order to further boost the performance of transfer learning, in several previous publications\[53, 54, 14\], new regularizers has been comprehensively investigated w.r.t. both model parameters and features. In \[53\], the convolutional weights are penalized to be closer to the source parameters rather than zero to avoid information loss from source data. Li et al.\[54\] utilize attention mechanism to restrict the difference between the convolutional features at same hierarchy from source model and target one, respectively. Further, Chen et al.\[14\] claim that feature components corresponding to small singular values would an impediment for knowledge transferring, and then propose to suppress such components as a regularization during fine-tuning. In this work, we also take advantages of Singular Value Decomposition on the features before softmax layer, and provide empirical analysis towards the learning mechanism during the learning process.

### 3 Experimental Setup

#### 3.1 Datasets

We conduct extensive experiments on several representative natural image classification datasets and one medical dataset. All the pre-training is implemented based on ImageNet\[2\].

- **CIFAR10\[16\]** and **CIFAR100\[16\]** are two fundamental datasets in computer vision community. Both of them contain 50,000 training samples and 10,000 test samples, and all the samples are evenly distributed in each category. CIFAR10 consists of 10 common classes of objects. CIFAR100 include 10 superclasses and each superclasses is made up of 10 fine-grained categories, and the size of each sample is $32 \times 32$.

- **Food-101\[55\]** is a challenging food classification dataset, which consists of 101 categories. There are 250 clean test images for each class and 750 training images containing some noisy labels.

- **FGVC Aircraft\[56\]** is a fine-grained dataset for aircraft classification. It contains 10,000 images of 100 categories of aircraft, and the training set is 2/3 of the whole dataset.

- **Stanford Cars\[57\]** contains 196 classes of fine-grained cars, and there are 8,144 and 8,041 samples in training set and test set, respectively.

- **CUB-200-2011\[58\]** is a fine-grained bird classification dataset containing 200 species. There are 11,788 training samples and 5,894 test samples. Annotation of bounding box, rough segmentation, attributes are provided.

- **Oxford 102 Flowers\[59\]** contains 200 common species of flowers in United Kingdom. Each of the category has 40 up to 258 images. There are 2,040 training samples as well as 6,149 test samples.

- **MIT Indoor 67\[60\]** contains 67 indoor scene categories with in total 15,620 images, and 80% images are used for training.

- **NIH Shenzhen CXR\[61\]** is a commonly used frontal-view chest Xrays dataset, consisting of 662 Xrays images. There are 326 normal cases and 336 abnormal ones with manifestations of Tuberculosis. We randomly choose 30% data for training, and the rest for evaluation.

#### 3.2 Pre-training Setup

In pre-training, we borrow the official PyTorch implementation for ImageNet training. The total number training epochs is set to 90. Stochastic gradient decent with momentum 0.9 is used to update the model parameters. The initial learning rate is 0.1 and are multiplied by 0.1 every 30 epochs. The weight decay is 1e-4. In this paper, we conduct most of the experiments with ResNet-50\[15\] to validate our claim.
Figure 2: Transfer learning performance on selected datasets. We can observe obvious different trends w.r.t. pre-trained epoch for FE and FT. The FT generally grows with the pre-training epochs increasing, while FE regularly reaches the peak at a middle epoch.

### 3.3 Transfer Learning Setup

In transfer learning, we use different training configuration to adapt to different dataset. For CIFAR10 and CIFAR100, in both FE and FT, the total training epoch is set as 150. The initial learning rate is 0.1 and is decayed by 10 times every 50 epochs. The optimizer is Adam\[62\]. For the rest natural datasets, we run 6,000 iterations and 9,000 iterations for FE and FT, respectively; the learning rate is set to 0.1 for FT and 0.01 for FE. And for Shenzhen, we only train 1,000 iterations for both setting with learning rate 0.01 for FT and 0.001 for FE, respectively.

### 4 Results and Analyses

In this section, we showcase all the experimental results of the transfer learning in two different settings: 1. Utilizing the pre-trained models as a feature extractor (FE) and retraining a softmax classifier; 2. Fine-tuning (FT) the whole model. We present experimental results of FE and FT in Section 4.1 and 4.2 respectively. A key observation is that, inadequately pre-trained checkpoints transfer better for FE. Besides, we find that a better FE, which can be viewed as a better initialization for the target model, does not yield a better fine-tuning result. This is confirmed in Section 4.3 by t-SNE\[63\] visualization of deep features before the classifier. In Section 4.4, we manage to discover the in-depth learning mechanism during fine-tuning and empirically explain the aforementioned paradox, with the help of spectral components analysis.
4.1 Inadequately pre-training brings better feature extractor

Concretely, in Figure 2, we can easily observe that there exists a best transferring spot before the model is fully pre-trained when viewed as a feature extractor for different datasets, which means that the correlation between the accuracy of the pre-trained model and the quality of the feature of penultimate layer is not as positive as claimed in [11]. We can also notice that the general trace of the FE performance is roughly a U-form curve with respect to the source performance, implying a potential trade-off between multiple factors during the pre-training process. Some curves exhibit a form of double-U, e.g. Stanford Cars and CUB-200-2011, and the FE performance at pre-trained epoch 40 and 70 is more likely to increase. We suspect this phenomenon may relate with the learning rate annealing after the 30-th and 60-th pre-training epoch [12].

4.2 Fully pre-training brings better fine-tuning performance

The case for FT is quite different compared with FE. The general evolution trend for fine-tuning is still positively correlated with the source performance, though the fully pre-trained checkpoint is not always the best. And we can also find that the best FT model emerges later than the best FE model. This asynchronization is actually surprising because it is a common sense that a better initialization should bring better fine-tuning results. However, our work is not the only one that challenges this intuition. Recent empirical studies [64, 65] propose to improve fine-tuning by re-initializing top layers, i.e. employing a worse feature extractor as the starting point of fine-tuning.

4.3 Visualization of the difference between the best FE model and the fully pre-trained one

In this subsection, we empirically visualize deep features of the best FE model (at 5 epoch) and the fully pre-trained one (at 200 epoch). The model is pre-trained on CIFAR10 and then transferred to MNIST, by both FE and FT. Deep features on the last convolutional layer of ResNet-18, produced by MNIST images, are extracted and dimensionally reduced to a 2-d space with t-SNE [63]. The FE performances are 96.47% and 88.47%, and the FT performances are 99.30% and 99.46% (in this experiment we use the full version of MNIST). As can be seen from the top two plots in Figure 4, the visualization result is consistent with the transferring performance. When directly using the pre-trained model to extract features, data points in embedding space of the 5-epoch model are clustered better, especially for categories corresponding to index 1 and 6; while fully pre-trained model produces a more chaotic feature distribution that many data points are entangled with their incongruent neighbors. However, the situation becomes reversely when the whole model is fine-tuned. There exist couples of misclassified data points in the feature space of 5-epoch model, while the fully pre-trained model provides highly tight and discriminative features. This phenomenon is somehow surprising because this means a better initialization, i.e., more discriminative features, could lead to worse fine-tuning performance.

4.4 Spectral Component Analysis

Based on the observations from Figure 2, two questions naturally arise: 1. What makes an inadequately pre-trained model a better feature extractor? 2. What makes a better initialization (FE) perform worse than a fully pre-trained model which could not produce more discriminative features at the beginning? To answer these questions, we resort to spectral analysis by Singular Value Decomposition (SVD) for an in-depth investigation. Specifically, we first obtain the batched feature matrix before the classification layer, which we denote as \( F \in \mathbb{R}^{b \times d} \), where \( b \) is batch size and \( d \) is feature dimension. After this, we decompose the matrix using SVD as:

\[
F = U \Sigma V^T, \tag{1}
\]

where \( U \) and \( V \) are left and right singular vectors respectively, and \( \Sigma \) is a rectangular diagonal matrix with the singular values on the diagonal. For convenience, we assume that all singular values are sorted in a descending order.

Then we divide the diagonal matrix \( \Sigma \) as the main matrix \( \Sigma_m \) and the residual matrix \( \Sigma_r \). To achieve this division, we first calculate the sum over all singular values as \( S^K_m = \sum_{i=1}^{K} \sigma_i \), and then determine the minimum \( k \) that satisfies \( S^K_m / S^K_r \geq 0.8 \). \( \Sigma_m \) preserves top \( k \) lines of \( \Sigma \) and fills the remaining elements with zero. \( \Sigma_r \) is then obtained by \( \Sigma_r = \Sigma - \Sigma_m \). In this way, we can get two spectral components \( F_m \) and \( F_r \) of the original \( F \) by truncated SVD reconstruction as

\[
F_m = U \Sigma_m V^T, \tag{2}
\]

and

\[
F_r = U \Sigma_r V^T. \tag{3}
\]
Figure 3: T-SNE visualization of features extracted before the classifier, before and after fine-tuning. Models are pre-trained on CIFAR10 and transferred to MNIST. The 5 epoch pre-trained model provides a better feature distribution on MNIST than the fully pre-trained one, but after fine-tuning for 50 epochs, the fully pre-trained model surpasses the 5 epoch one, generating more discriminative inter-class features and more compact intra-class features. Best viewed in color.

Table 1: Results of Spectral Component Analysis for the best FE models and fully pre-trained one. SE denotes pre-training epoch on CIFAR10, and SA means the pre-training accuracy. FE means viewing the pre-trained model as feature extractor and only retraining a softmax classifier; FT means fine-tuning the whole model. The 96.47% means the MNIST accuracy of 5-epoch model in FE task, and the 88.24% means the classification accuracy on top of $F_m$. We can observe that $F_m$ and $F_r$ perform differently no matter trained with more source information (pre-training) or more target one (fine-tuning):

| Task | SE(SA) | 5 epochs (70.24%) | 200 epochs (95.32%) |
|------|--------|-------------------|---------------------|
|      |        | $F_m$ 88.24%     | $F_m$ 88.47%        |
|      |        | $F_r$ 55.45%     | $F_r$ 58.74%        |
| FE   | 96.47% |                    |                     |
|      |        | $F_m$ 88.24%     | $F_m$ 99.26%        |
|      |        | $F_r$ 55.45%     | $F_r$ 54.69%        |
|      | 99.30% |                    |                     |
|      | $F_m$ 99.26% |                | $F_m$ 99.08%        |
|      | $F_r$ 27.77% |                | $F_r$ 71.28%        |

According to [14], $F_m$, as the main components of the feature matrix, represent the majority of transferring knowledge of the extracted features, while $F_r$ is untransferable components or is hard to transfer that may do harm to the learning process and further causes negative transfer[66]. To evaluate the two components, we retrain a softmax classifier with Gaussian initialization on top of $F_m$ and $F_r$ for 50 epochs. We set the batch size as 128, using Adam[62] optimizer and learning rate as 0.01.

For comparison, we choose the best FE model and the fully pre-trained model in this experiments. For convenience, we call the feature from the best FE model as BFE feature and the feature from fully pre-trained model as FP feature. The first model pairs are from CIFAR10-to-MNIST experiment, and the results are shown in Table[1]. Since we only analyze the features before the softmax layer, the FE models are actually identical to the corresponding pre-trained models; the FT models are fine-tuned with MNIST for 50 epochs. The best FE model is the 5-epoch pre-trained model, whose accuracy is 96.47% and is 8% higher than the fully pre-trained one; however, after fine-tuning, the fully pre-trained model outperform the 5-epoch one, even with less discriminative initial features. Thus, we decompose the
Figure 4: Evolution of the spectral components in pre-training from 5 epoch to 200 epoch. The orange curve represents the main components $F_m$, and the blue one represents the residual $F_r$. It is noticeable that $F_m$ becomes less discriminative when the pre-training epoch grows. Since $F_m$ represents the most transferable knowledge, this drop can also be an explanation of why fully pre-trained model cannot provide better features.

BFE feature and FP feature to investigate which part of components contribute to their higher performance in FE and FT, respectively.

As can be seen from Table 1, there are several interesting discoveries as followed.

- **The quality of $F_m$ is responsible for the FE performance, while $F_r$ is dominant when fine-tuning the whole model.** Specifically, we find that the 5-epoch model performs better as FE due to its remarkable superiority in $F_m$. However, in the FT setting, the 5-epoch and 200-epoch model show similar performances in $F_m$, and the higher $F_r$ results in higher overall performance of the 200-epoch model.

- **As pre-training fits source data, $F_m$ becomes less discriminative on target data, but $F_r$ transfers better** (observed from the line of FE in Table 1). The degeneration in transferability of $F_m$ could be caused by domain discrepancy between source and target data, as fully fitting source data may convert general patterns to those specific to the source domain. On the contrary, since $F_r$ can not be well learned at earlier pre-training stages, it generally becomes more informative by further pre-training.

- **For FT, $F_m$ is easily adapted to target data, but $F_r$ becomes less discriminative on target data** (observed from each column in Table 1). Both the 5-epoch and 200-epoch model achieve very high $F_m$ performance (99.26% and 99.08%) after fine-tuning. This imply the underlying learning mechanism that DNNs prefer a prior fitting with main spectrums rather than residual spectrums. The performance of $F_r$ (from FE to FT) decreases due to the information capacity w.r.t. entire $F$ is constant. Despite the degeneration, better $F_r$ in FE still delivers better $F_r$ after fine-tuning, indicating that the residual components learned from source data are not completely forgotten after fine-tuning on target data.

There might exist another explanation for the phenomenon in this spectral components analysis, which is from the perspective of frequency domain. We can view $F_m$ as low-frequency components of the original $F$, and $F_r$ as the high-frequency one. Couples of previous publications have revealed that the neural networks are inclined to learn low-frequency information first in the training process [67, 68, 69]. In our case, during pre-training, the model rapidly learns low-frequency knowledge at the early 5 epochs, which makes it a best feature extractor for downstream tasks. When keep learning in the source domain, more high-frequency patterns, which are specific to the source domain, are gradually learned; therefore, negative transfer happens.

We also illustrate the evolution of the classification performance of the two components for different pre-training epochs in the FE task (from CIFAR10 to MNIST) in Figure 4. It can be obviously noticed that $F_m$ and $F_r$ shows exactly opposite trends when pre-training epoch increases. With longer pre-training on CIFAR10, $F_m$ becomes less discriminative, since the model is prone to a deeper fitting to CIFAR10 with more high frequency knowledge learned. Inversely, the residual components $F_r$ becomes more informative for target data when memorizing more source knowledge.
Figure 5: LogME results for CIFAR10 and CIFAR100 in both FE and FT. The Rank Correlation means Kendall’s \( \tau \) coefficient. It can be observe that LogME best capture the correct ranking for CIFAR10 in FE, and totally failed to assess the CIFAR100 performance w.r.t. different checkpoints.

4.5 The correlation between the transferability assessment and the accuracy of fine-tuning on fixed features

In this subsection, we utilize the state-of-the-art transferability assessment tool Log of Maximum Evidence (LogME)[18] to validate whether it is possible to obtain the best checkpoint during pre-training without any training. LogME is proposed to calculate the correspondence between the feature before the softmax layer and the target label. We compute LogME score for three datasets at different pre-trained checkpoints, and calculate the correlation coefficient and Kendall’s \( \tau \) coefficient[70] for both FE and FT performance. As can be seen in Figure 5, LogME fails to correctly rank the performance for both FE and FT, and the LogME score has an obvious inverse correlation with both two transfer settings in CIFAR100.

5 Discussion and Future Work

Better performance in source task has long been believed to be more beneficial in target tasks. However, in this paper, we find that when using pre-trained models as feature extractors and retraining a new softmax classifier, the transferring performance does not agree with the source accuracy. There always exists a best epoch in the pre-training process. Intuitively, this is possibly brought by the distribution gap between the source and target data, forming a trade-off between source and target knowledge. If pre-training less, no sufficient (general) visual knowledge can be obtained and the feature is suboptimal; but negative transfer happens on the other way around. Based on this observation, we can operate a more sophisticated checkpoint selection process when we need a good feature extractor trained from source data[5].

Moreover, a common sense that better initialization should bring better training results is challenged given our observations. As can be seen from the difference of the evolution along the pre-training epochs between FE (view pre-trained model as a feature extractor) and FT (fine-tune the whole model), the FT performance still has a high
correlation with the source performance, regardless of the U-property of FE performance. This means that a better feature extractor, which can be viewed as a better model initialization, does not definitely bring a better fine-tuning result. Further, in order to provide a more insightful explanation, we conduct a comparative experiment between the best FE model and the fully pre-trained one. Specifically, we delve into the spectral components of the feature before the classification layer, and find that the components from top singular values contribute most to the FE, while the components with small singular values plays a more critical role for the FT performance with fully pre-trained model, since the FE are already highly discriminative for both models. In previous research[14], spectral components corresponding to small singular values are criticized as hard to transfer or even untransferrable. Concretely, we reach consistent conclusions but take different operation. Unlike [14], we do not drop the residual component, but investigate its discriminativeness along with the main component. In this way, we empirically reveal the reason behind the paradox phenomenon that better feature extractor fails to produce better fine-tuning results in the end. Consistent with an intuitive assumption that over-pre-training would undermine the performance of the pre-trained model as a feature extractor, we discover the main component of target feature becomes impaired due to the model overfitting to source data with pre-training epoch increasing.

From a different perspective, we regard the main components as containing low frequency knowledge of the feature, and the residual components as the carrier of high frequency information. This makes sense since the residual components are generated from smaller 20% singular values, which are of high variation. In this way, our discoveries are also consistent with what have been well studied in training mechanism of deep neural networks that the deep models learn low frequency components before capturing high frequency ones[67–68].

However, there are still some phenomena beyond our explanation in Table[1] For example, since the performance of $E_m$ decrease with more pre-training (from 88.24% to 58.74%), what makes it grow much faster (40.34% vs. 11.02%), though the accuracy is a little bit lower (99.08% vs. 99.30%), when trained with target data? It is attractive to keep investigating the correspondence between different spectral components and different learning stage (e.g., early or late in pre-training, pre-training or fine-tuning). We believe such research is beneficial for designing new regularizers for better transfer learning. Furthermore, whether it is the same case in other pre-training paradigm, such as contrastive self-supervised learning, also deserves to be learned. And new assessment tools should be developed since the SOTA LogME fails to select the best pre-training checkpoint. We leave these topics to future work.

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