Multifaceted Analysis of Fine-Tuning in Deep Model for Visual Recognition

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In recent years, convolutional neural networks (CNNs) have achieved impressive performance for various visual recognition scenarios. CNNs trained on large labeled datasets can not only obtain significant performance on most challenging benchmarks but also provide powerful representations, which can be used to a wide range of other tasks. However, the requirement of massive amounts of data to train deep neural networks is a major drawback of these models, as the data available is usually limited or imbalanced. Fine-tuning (FT) is an effective way to transfer knowledge learned in a source dataset to a target task. In this paper, we introduce and systematically investigate several factors that influence the performance of fine-tuning for visual recognition. These factors include parameters for the retraining procedure (e.g., the initial learning rate of fine-tuning), the distribution of the source and target data (e.g., the number of categories in the source dataset, the distance between the source and target datasets) and so on. We quantitatively and qualitatively analyze these factors, evaluate their influence, and present many empirical observations. The results reveal insights into what fine-tuning changes CNN parameters and provide useful and evidence-backed intuitions about how to implement fine-tuning for computer vision tasks.

 $\label{eq:ccs} Concepts: \bullet \textbf{Computing methodologies} \rightarrow \textbf{Computer vision}; \textbf{Image representations}; \textbf{Object recognition}; \textit{Neural networks}.$

Additional Key Words and Phrases: Deep learning, convolutional neural network, image classification, fine-tunining

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1 INTRODUCTION

Visual recognition is a fundamental concern of computer vision in the big data age. Over the past years, it has achieved significant progress due to the rapid development of ubiquitous sensing technologies of collecting image data and the available of large computational resources to train big models. One of the huge successes is deep convolutional neural networks (CNNs), which have achieved excellent performance on large number of visual tasks, such as recognition [17–19, 22–24, 26, 28, 46–48], object detection [11, 12, 41, 43], segmentation [21, 31] and so on. These models are mainly built upon the convolution operation, which extracts discriminative and informative features by gradually integrating spatial and channel information within local receptive fields. In this manner, they learn visual representations layer-by-layer,

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Fig. 1. Factors that influence the performance of fine-tuning.

where low features (e.g., color blobs, edges and simple shapes, which are applicable to many datasets and tasks) are general and high layer features are specific, which depend much on the target dataset and task [58].

Krizhevsky *et al.* [26] firstly train *AlexNet* [26] on ImageNet for the large scale visual recognition challenge in 2012 (ILVRC 2012) [42]. Their successes are that they can not only obtain significant performance on most challenging datasets [42, 61], but also provide powerful representations which can be used to other tasks or different datasets [7, 9, 14, 44, 57]. After this, CNNs have been successfully applied to numerous visual tasks. The approaches employing CNNs can be divided into two categories according to whether having abundant data to train deep neural networks.

With the available of large annotated target datasets such as ImageNet [42], Places [61], the first way is to directly train a model from scratch on the target dataset. After the success of *AlexNet* [26], many complex architectures have been proposed such as *VGGNet* [46], *GoogLeNet* [48], *ResNet* [18], *SENet* [22] and so on. These high-capacity models have brought excellent progress by mainly increasing network depth, width, as well as enhancing connection between different layers and channels of feature maps. For example, Symonyan *et al.* [46] investigate the effect of network depth with the recognition accuracy and propose a 19-layer architecture which outperforms previous neural networks with a huge margin. Hu *et al.* [22] focus on the channel interdependence in feature maps and propose *SENet* [22] which has obtained the best performance in ILSVRC 2017. Luan *et al.* [33] propose Gabor Convolutional Networks (GCNs) which incorporate gabor filters to CNNs to enhance deep feature representations with steerable orientation and scale capacities. Wu *et al.* [55] propose a model to learn unified hash codes as well as deep hash functions. Liu *et al.* [29] design a multi-scale architecture based on the network simulation of wavelet multi-resolution analysis. Wu *et al.* [56] introduce a deep model which integrates deep convolutional networks with binary latent representation learning. Li *et al.* [27] combine CNN and recursive neural network (RNN) for visual recognition. Wu *et al.* [54] propose a model where feature learning and hash function learning are jointly integrated.

However, for many object recognition or scene classification datasets, there are always not so many available labeled images to feed such big models. For these situations, the second way is to just employ a pre-trained CNN as a feature Manuscript submitted to ACM

extractor. Approaches of this category firstly take the whole image as the input for a pre-trained CNN to extract high layers activations as image representations and then utilize them to train simple classifiers to obtain recognition results. The combination of deep representations and a simple classifier has been a preferred solution for many visual recognition tasks [7, 9, 14, 30, 44, 57]. For example, Donahue *et al.* [9] suggest that the deep CNN trained on ImageNet is an effective feature extractor and provide large evidence to support this claim. Gong *et al.* [14] utilize CNN to extract local patch features at multiple scale, and then pool them to image-level features. Their method harvests deep activation features and obtains significant performance on many datasets. Liu *et al.* [30] also reveal that the activations of convolutional layers are useful image representations.

Although directly using activations of a pre-trained model has good performance for many tasks, fine-tuning a pre-trained model on one target dataset can further improve the performance by making the features more specific to the target task [1, 7, 12, 15, 16, 36, 52, 62]. Girshick *et al.* [12] remove the specific 1000-category classification layer of a CNN which is trained on ImageNet, and replace it with a randomly initialed (N+1)-category classification layer (where N is the number of categories in the target data set, and the extra one category is for the background). To learn the new parameters, they retrain the modified model on the extracted region proposal dataset, with unchanged parameters initialized from the pre-trained one. Their work indicates that fine-tuning is fruitful. Chafield *et al.* [7] present rigorously comparisons of the hand-crafted features, CNNs-based features, and CNNs-based features after fine-tuning on many datasets. Their work indicates that the fine-tuned CNNs-based features outperform the others by a large margin. The work of Agrawal *et al.*[1] and Gupta *et al.* [15] also demonstrates that fine-tuning a per-trained CNN can significantly improve the performance.

In order to employ the *inherent knowledge* of a CNN which trained on a big source dataset, it is intuitive to apply fine-tuning as it is a reasonable and effective way to make full use of a per-trained model and alleviate the scarce of training data. In this paper, we explore factors that influence the performance of fine-tuning, as illustrated in Fig. 1. There are many factors that influence the performance of fine-tuning, which include parameters for the retraining procedure (e.g the initial learning rate of fine-tuning), the distribution of the source and target data (e.g., the number of categories in the source dataset, the distance between the source and target datasets) and so on. To address the problem of how to fine-tune properly to obtain satisfactory performance on different classification tasks with various target datasets, in this work, we quantitatively and qualitatively analyze these factors respectively. We artificially select different source and target datasets with different constraints, and then conduct fine-tuning on these datasets. To the best of our knowledge, this is the first time to investigate these factors systematically. The main empirical observations include the following aspects:

First, with roughly the same distance to the target dataset, the bigger of the number of categories in the source dataset, the better performance fine-tuning obtains. The pre-trained procedure works as a regularization to make a better generalization from the source dataset. For a fixed target dataset, the more categories the source dataset has, the more knowledge is learned. More categories make the pre-trained model have better generalization ability, bringing better performance of fine-tuning.

Second, when the source dataset is fixed, the performance of fine-tuning increases with more training examples exposed to the retraining of the pre-trained model. What is more, the gain of fine-tuning versus training network from scratch decreases with the increase of retraining examples. With more training examples, the parameters in different models both are adjusted to fit the target data, so the difference decreases.

At last, we manually select source datasets which contain the same number of categories but have different similarity to the target dataset. The results show that the more similar between the source and target datasets, the better Manuscript submitted to ACM performance fine-tuning obtains. We analyze the characteristic of different models at both filter-level and layer-level, and show their sensitivities to the target dataset. We also qualitatively show the differences among these different models.

In the following we give a brief overview of related work in Section 2. Section 3 and Section 4 present our experimental settings and results. At last, we give our conclusion in Section 5.

2 RELATED WORK

Our work is related to the work of exploring the transferability of pre-trained deep models. In this section, we briefly review the related work about unsupervised pre-training, domain adaptation and transfer learning.

2.1 Unsupervised Pre-training

Greedy layer-wise pre-training of unsupervised learning followed with global fine-tuning of supervised learning is an essential component for deep learning, as the pre-training procedure can introduce useful prior knowledge. The training strategies for deep models like deep belief networks (DBN) [20], stacked auto-encoders (SAE) [6] and stacked denoising auto-encoders (SDAE) [51] are both based on such a similar approach: First, each layer learns a transformation of its input independently. Second, all the parameters are fine-tuned with respect to a training criterion. Compared with randomly initialized approaches, the gain obtained through pre-trained is impressive. The effect of unsupervised pre-training can be explained as regularization, and it guides the learning towards basins of attraction of minima that support better generalization from the training examples [10]. Whereas, in the conventional training procedure of CNNs, there is no unsupervised pre-training stage. However, when fine-tuning a pre-trained CNN model on a target dataset, we can regard the supervised pre-training as a substitution of the unsupervised pre-training. In this paper, we empirically show the influence of various factors when conducting fine-tuning.

2.2 Domain Adaptation

Domain adaption focus on how to deal with data sampled from different distributions [4, 38] (e.g., from product shot images to real world photos), thus compensating for their mismatch. Since the theoretical analysis by [5], there have been a lot of research related with this area [8, 13, 50]. Glorot *et al.* [13] demonstrate that the features extracted from SDAE are beneficial for the domain adaptation. Chopra *et al.* [8] propose a method which learns image representations with respect to domain shift by generating a lot of intermediate datasets, which are obtained by interpolating between the source dataset and the target dataset. More similar to our work, Tzeng *et al.* [50] propose a new CNN with a new adaptation layer and an auxiliary domain confusion loss to learn domain-invariant representation. Long *et al.* [32] propose Deep Adaptation Networks (DANs) to learn transferable features with statistical guarantees. Their proposed method can also scale linearly by unbiased estimate of kernel embedding. The aim of our work is to study the factors involved to fine-tuing but not to obtain the best performance. We focus on one fixed architecture (i.e., AlexNet) and conduct experiments on subdatasets which are manually selected from the ImageNet [42] dataset. Our experiments are dedicated to analyzing the factors that influence the performance of fine-tuning.

2.3 Transfer Learning

Transfer Learning focuses on the possibility to utilize useful knowledge learned from a source task to master a target task [37]. Different from domain adaptation, an essential requirement for successful knowledge transfer is that the source domain and the target domain should be closely related [38, 39]. Transfer learning has received much attention Manuscript submitted to ACM

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Fig. 2. The parent classes of the banana class and the beagle class. The green leaf nodes are the target classes, and the blue root node is the entity class which is the root of WordNet. The red nodes are the middle classes through which the leaf nodes can reach the root (Best viewed in color).

recently and many approaches based on CNNs have been proposed in the computer vision community [2, 16, 35, 58, 59]. The knowledge transferred from CNNs can be categorized into two kinds. The first one is in the form of feature representations. These approaches use a per-trained CNN as a feature extractor and then directly utilize these extracted features for the target task [7, 9, 44]. The second one is in the form of model parameters. Oquab *et al.* [35] propose a framework that remove the output layer of CNN and add an additional module formed by two fully connected layers. Their work indicates that this procedure is an effective way to use the knowledge in a per-trained model. Yosinski *et al.* [58] study the transferability of CNNs in each layer. Wang *et al.* [53] reuse the parameters of a pre-trained model and added new units to increase its depth and width. Most similar to our work, Azizpour *et al.* [2] investigate many factors affecting the transferability of CNNs such as the width and depth of different architectures, the diversity and density of training data and so on. While fine-tuning is just one investigated issue in their work. In this work, we systematically analyze the factors that affect the performance of fine-tuning based on one model with a fixed structure and shed light on the inner working mechanism of fine-tuning.

3 EXPERIMENTAL SETUP

The architecture of the convolutional neural network in our experiments is almost the same with the one proposed by Krizhevsky *et al.* [26]. It has five convolutional layers and three fully-connected layers. Table 1 details the structure and parameters of it. In our experiments, we train and fine-tune the CNN with the Caffe open-source framework [25].

For training the model on the source dataset, the learning choices are the same with [26]. The weights in each layer are initialized from a zero-mean gaussian distribution with deviation 0.01, except the deviations of layer fc6 and fc7 are 0.005. The neuron biases in conv2, conv4 and conv5, as well as all the fully-connected layers are initialized with the Manuscript submitted to ACM



Fig. 3. The tree structure of 1000 ImageNet classes. The green leaf nodes are the classes in the 1000 ImageNet classes. The red nodes are the middle classes through which the leaf nodes can reach the root. The blue root node is the entity class which is the root of WordNet (Best viewed in color).

Table 1. The architecture of the CNN used in our experiments. C indicates convolutional layer. R indicates nonlinear layer with the activation function of Relu. P indicates max pooling layer. N indicates normalization layer. FC indicates fully-connected layer.

layer	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
name	C1	R1	P1	N1	C2	R2	P2	N2	C3	R3	C4	R4	C5	R5	P5	FC6	R6	FC7	R7	FC8
type	С	R	Р	Ν	С	R	Р	Ν	С	R	С	R	С	R	Р	FC	R	FC	R	FC
channels	96	96	96	96	256	256	6256	6256	5 384	384	384	384	256	256	5256	4096	4096	4096	4096	1000
size	11	-	3	-	5	-	3	-	3	-	3	-	3	-	3	-	-	-	-	-
parameters	11712	-	-	-	6656	-	-	-	3840	-	3840	-	2560	-	-	37752832	-	16781312	-	4097000
percentage	0.0199	7			0.01135	i			0.006546	,	0.006540	5	0.004364			64.36		26.61		6.984

constant 1, while the biases in other layers are initialized with the constant 0. The momentum is 0.9 and the weight decay is 0.0005. The learning rate at the beginning is 0.01 (for training models from scratch) and after every 20 cycles it is divided by the constant 10. We train the CNN for roughly 100 cycles. To reduce overfitting, first there are two dropout layers with a dropout ratio of 0.5 followed the layer of fc6 and fc7. Second, we randomly crop 227×227 pixels from the 256×256 input image and randomly mirror it in each forward and backward processing.

For fine-tuning the pre-trained model on the target dataset, we remove the last fully-connected layer which is specific to the source task and replace it with a new randomly initialized one with C units (where C is the number of categories in the target task). After this we use stochastic gradient descent (SGD) to continuously train (i.e., retrain) the modified model on the target dataset. In contrast to the work in [58], the parameters copied from the pre-trained model are optimized with respect to the target task in our experiments, while these transferred parameters are fixed during retraining in their work.

We analyze the factors that affect fine-tuning mainly on the 1000 ImageNet classes [42] dataset (ILSVRC2012), as shown in Fig. 3. It totally has 1.28 million images with abundant semantic diversity and density. In order to find subdatasets with different distances (for example, A is a dataset which just contains domestic dogs, B is a dataset which contains many other animals such as cats, sheep, while C is a dataset which contains many traffic instruments. We define the distance between A and B is smaller than the distance between A and C qualitatively, as objects in A and B both have eyes, legs and tails while objects in C do not have), we draw out the tree structure of 1000 ImageNet classes according to WordNet [34]. For every category in the 1000 classes, it belongs to one synset in WordNet. We can find its parent classes recursively until reaching the node of entity which is the root of the WordNet. For example, the parent classes of the "n02088364 beagle" class and the class of "n07753592 banana" are showed in Fig. 2. The tree structure of the whole 1000 classes is illustrated in Fig. 3. In the following of our paper, we select subdatasets from the 1000 ImageNet classes with different constraints.

4 THE FACTORS THAT AFFECT THE PERFORMANCE OF FINE-TUNING

There are many factors that affect the performance of fine-tuning, such as the number of categories in the source dataset, the distance between the source and target dataset, the number of categories in the target dataset, the number of training examples per category in the target dataset and so on. In our paper, we individually analyze the effect of each factor. For training models from scratch and fine-tuning models from pre-trained ones, we use all the images (which belong to the selected categories) in the training set of ImageNet. We first train a set of models on different datasets and then fine-tune these model on the target datasets. For testing, we use 50 images per category, which are the same with the validation set of ImageNet.

4.1 The Initial Learning Rate of Fine-tuning

Fine-tuning is implemented by initializing a network with parameters optimized on one source dataset except the last task-specific layer which is randomly initialized. Then, using the target training samples, the parameters of the network are updated. When using stochastic gradient descent to optimized the weights, the initial Learning Rate (LR) has big influence on the learning procedure. As previous work has mentioned [2, 12], the initial LR at the beginning should be smaller than the initial LR used to optimize the wights on the source dataset. This strategy ensures the prior knowledge learned in the source dataset are not clobbered.

However, to what extent does the initial LR affect the fine-tuning performance? In this section, we experimentally investigate this factor. We randomly select 100 classes from the 1000 ImageNet classes as the target dataset. And then, Manuscript submitted to ACM

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Fig. 4. The effect of the initial learning rate on the performance of fine-tuning. The first column is the performance on the test set when fine-tuning the pre-trained model with different initial Learning Rates (LRs). The second column is the training error (i.e., training loss). The third and fourth columns are the average accuracy and the average training error. The experiments are conducted independently for five times.

we train the model from scratch on the remaining 900 categories. After this, we fine-tune the pre-trained model on 100-class target dataset with decreasing initial Learning Rates: 0.01, 0.005, 0.001, 0.0005 and 0.0001. The experiments are conducted independently for five times (i.e., five target datasets and five source datasets). The results are shown in Fig. 4. When the initial LR is set to 0.02 or bigger, the learning procedure does not converge as we have tried in our experiments. So we set 0.01 as the biggest initial LR. The remarkable observations are: (1) Bigger initial LRs bring smaller training errors. (2) Starting with a big initial LR, there are some bumps in the early training epochs. This indicates the basins of attraction of minima are reconstructed. Though the training error is much smaller, the generalization ability is worse, as the test accuracy is not good enough compared with a moderate initial LR. (3) When starting with a very small LR, the training error is much bigger and the test accuracy is smaller. This indicates the learning procedure is not plenitudinous. When starting with the initial LR of 0.001, the learning procedure is mild, and it obtains the best performance. So in the rest of our experiments, we fixed the initial LR with 0.001.

4.2 The Number of Categories in the Source Dataset

Previous work has suggested that increasing the training data can significantly improve the performance [2, 35]. In this section, we investigate the effect of the number of categories in the source dataset for fine-tuning. First we randomly select 100 categories from ImageNet as the fixed target dataset. And then, we randomly select 800, 500, 200, 100, and 80 categories respectively from the remaining categories as different source datasets. Thus, the distances between these source datasets and the target dataset are roughly the same.

After obtaining different kinds of pre-trained models which are trained on these selected source datasets, we fine-tune these models on the fixed target dataset. Fig. 5 is a plot of the accuracy and training error when fine-tuning different pre-trained models on a fixed target dataset. We also conduct the experiments independently for five times and Table 2 is the the average performance. There are several observations can be drawn from these results. Manuscript submitted to ACM



Fig. 5. The effect of the number of categories in the source dataset when fine-tuning from different pre-trained models on the fixed target dataset. The first column is the accuracy and the second column is the training error (i.e., training loss). The third and fourth columns are the average values. We run the experiments with the same settings for five times.

First, when we fine-tune a pre-trained model on a dataset, it dramatically converges faster than training it from scratch, especially when the sour dataset has many categories. The explanation is that the model pre-trained on dataset which contains enough categories has a better basin of attraction of minima, and its parameters can be efficiently adapted to new tasks with little changes.

Second, as expected, a network trained on more categories, it learned more knowledge, and the generalization ability of the network is much better. As we can seen in Fig. 5, with the decrease of the number of categories in the pre-trained model, the performance of fine-tuning decreases and the training error goes larger. For example, the model trained on 1000 categories (N=1000) has the best performance and the training error is the smallest. When the pre-trained number of categories is 500 (N=500), the training error is larger and the performance decreases. But it is obvious that even though the training error (N=100) is larger, the performance is still better than the performance of training the network from scratch. When fine-tuning from itself (continued training on the target dataset itself), the training error goes smaller, but the test accuracy is almost the same with the accuracy of training the network from scratch.

At last, when fine-tuning from a deficient model which trained on a source dataset which only has s small number of categories (N=80), the performance is even worse than training the model from scratch. This can be attributed to the perishing generalization ability of the pre-trained model and the small learning rate of fine-tuning.

With roughly the same distance to the target dataset, the bigger of the number of categories in the source dataset, the better performance fine-tuning obtains, as shown in the results. It can be explained as that the procedure of pre-trained a model works as a regularization, making better generalization from the source dataset. The more knowledge learned in the source dataset, the better generalization ability the pre-trained model has.

4.3 The Distance between the Source and Target Datasets

It is well known that dataset bias is a very common issue in visual recognition [2, 49, 50, 58]. However, when fine-tuning pre-trained models on a target dataset, what is the relationship of the corresponding performance and the distance between the source and target datasets? It is meritorious to expose what happens when fine-tuning from different Manuscript submitted to ACM



Table 2. The performance (mean and variance) of fine-tuning different pre-trained models on the fixed target dataset. We conduct the experiments respectively for five times.

Fig. 6. Different branches of the 1000 categories in ImageNet. The integer in the parenthesis indicates the number of the categories that the branch contains. The number in the beginning of the node is the corresponding WordNet ID.



Fig. 7. Images belong to different branches. The first row shows images belong to the super class of dog (e.g., rhodesian ridgeback, papillon, and saint bernard). The second row shows images which are the rest of the living_thing super class (e.g., plant, platypus, kangroo, and wolf) except the dog class. The third row shows the super class of instrumentality (e.g., lock, fishing pole, and mouse) and the last row shows images which belong to the rest of the artifact super class (e.g., cloth_covering, food) except the instrumentality class.

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		near_DOG	far_DOG	scratch
DOC	CNN	59.56	55.94	55.62
DOG	SVM	58.26 (44.98)	55.14 (28.88)	55.38
		near_INSTRU	far_INSTRU	scratch
INSTRU	CNN	67.12	61.58	54.22
	SVM	66.70 (60.06)	61.00 (47.54)	54.00

Table 3. The performance of fine-tuning different pre-trained models on the target dataset (%). CNN indicates the accuracy which is the direct output of the CNN. SVM indicates the result of the features of layer fc7 and the combination of a SVM classifier. The performance before fine-tuning is reported in parentheses. Scratch represents the accuracy of training the model from scratch.

pre-trained models. In this section, we investigate this factor qualitatively and quantitatively and reveal insights into what happens when conducting fine-tuning.

Measuring the distance between two datasets is very crucial in image recognition. We consider the way used by Yosinski [58]. More precisely, we manually select nodes in different branches in the tree structure of the 1000 categories in ImageNet, thus forming subdatasets which have different distance to a fixed target dataset, as illustrated in Fig. 6. For example, the 1000 categories are divided into two branches, one is living thing which contains 451 categories, and another one is artifact which contains 549 categories. We first select two fixed datasets with 100 categories, and then select two datasets with different distance with 500 categories for each of the target dataset. The procedures to obtain the datasets are: (1) The dog branch has 118 categories (e.g., rhodesian ridgeback, papillon, and saint bernard), as shown in Fig. 7. Therfore, 100 categories are randomly selected from this branch as the first target dataset which is denoted as DOG. And then, we randomly select 500 categories from the 549 categories super class of artifact as a source dataset, which is denoted as far DOG. Near DOG is composed of the rest of the 400 (1000-100-500) categories and 100 categories randomly selected from far_DOG. The distance between near_DOG and DOG is smaller than the distance between far_DOG and DOG, as there are many categories in near_DOG which have eyes, legs, tail and fur (e.g., platypus, kangroo, and wolf) while categories in far_DOG do not have. (2) The second target dataset is selected from a more widely distributed way. As there are 347 categories in the instrumentality super class (e.g., lock, fishing pole, and mouse), 100 categories are randomly chosen as the target dataset which is denoted as INSTRU. The 451 categories super class of living thing and a random choose of 49 categories from the super class of cloth covering and food which contain 202 categories compose far_INSTRU. Near_INSTRU contains the rest 400 (1000-100-500) categories and 100 categories randomly selected from far_INSTRU.

The performance of fine-tuning different pre-trained models on the target dataset is illustrated in Table 3. In order to measure the representative and discrimination of different pre-trained models, we also utilize the features of layer fc7 and a simple SVM classifier to obtain the classification accuracy on the target dataset. It is can be obtained that the distance between the source and target datasets has much influence on the performance of fine-tuning. For DOG recognition, the features directly extracted from the model pre-trained on near_DOG (44.98%) is much better than that of far_DOG (28.88%). For the model which is pre-trained on the source dataset which is close to the target one, it learns prior knowledge which is useful to classify the target images. So near_DOG performs better than far_DOG. Even more, the performance of fine-tuning the model which is pre-trained on near_DOG (58.26) is also much better than the fine-tuned far_DOG (55.14), as expected. And the trend is the same in INSTRU. It is demonstrated that fine-tuning from a near model yields better performance than a far one. The results show that the more similar between the source and target datasets, the better performance fine-tuning obtains.



Fig. 8. The sensitivity of filters in the conv5 layer. The first row is for the class of *garbage truck*. The second and third rows are for the class of *forklift* and *pencil box* respectively. The red dash lines in the first column shows the most top-five filters in the model pre-trained on near_INSTRU (near) and the blue dash lines are for far_INSTRU (far). The red solid lins in the second cloumn are the most top-five filters after fine-tuning near on INSTRU (FT-near) and blue solid liens are for (FT-far). Red solid lines in the third cloumn are for FT-near and red dash lines are for near. The fourth cloumn shows top-five filters in all the five models. Specifically, the green solid lines are for the model trained on INSTRU itself (Self). The last cloumn shows the mean AP of the five filters for each model.



Fig. 9. The statistics of sensitivity percentages for different models on the 100 categories in INSTRU. Near represents the model first trained on near_INSTRU, and far indicates the fine model first trained on far_INSTRU. Self is the model directly trained on INSTRU from scratch.

4.3.1 The discrimination of individual filters. The discrimination of different layers indicate the class selectivity of the group of filters in the particular layer. Even though most of the features in convolution neural networks are distributed code, it is also important to measure the characteristic of individual filters, as cells in human brain have big response to some specific and complex stimuli, which has close relationships to object recognition [3]. The discrimination of one individual filter on one class can be regarded as its sensitivity to the class. More precisely, if a filter is sensitive to one class, the filter should fire strongly on all images in this class, and at the same time it should also have small response to images in other classes.

In order to measure the sensitivity of one filter for one class, we use the precision and recall curve to compute the criterion quantitatively, just as Agrawal do in [1]. Specifically, we analyze the filters on the conv5 layer, as features of this layer are mid-level image representations, which are the combination of low layer features and also have less semantic information compared to the features in fully-connected layers. The features of conv5 are consisted of responses of 256 filters, which have a size of $256 \times 6 \times 6$. We use max-pooling to transform the activations of spatial grid of size 6×6 to one value, as this strategy just causes a small drop in recognition performance while brings a shorter and more compact features. With this implementation, the responses of size $256 \times 6 \times 6$ are reduced to 256×1 , each element of which indicates the response of one filter. Now, for a set of images, we will get a set of associated scores. We treat every filter as a classifier and compute the precision recall curve for each of them.

For each class, we now can get 256 curves with each curve correspond to one filter. The curves are computed on the test set of INSTRU which contains 100 categories, with 50 images per class. We sort the filters in descending order of their average precision values (APs). Fig. 8 shows the top-fives filters of their precision recall curves for the class of *garbage trunk, forklift,* and *pencil box* respectively. For the *garbage truck* class, the top-five filters in the near model are Manuscript submitted to ACM

more sensitive than the filters in model of far, as the precision recall curves of far are almost under the precision recall curves of near. In order to compare one individual filter, we use the mean average precision (mAP) of the selected five filters as the sensitivity, as shown in last column of Fig. 8. The mAP of near is bigger than that of far. After fine-tuning, both of the mAPs for far and near obtain increase.

In order to compare these filters in different models in a global level, we calculate the number of categories that the filters in one model has bigger mAP than filters in the others. We use sensitivity percentages to evaluate the global sensitivity of two models when comparing them. The bigger of percentage that one model has, the more sensitive the model is. Fig. 9 shows the sensitivity percentages of different models on the 100 categories in INSTRU. There are many conclusions can be obtained from the results.

First, filters in near are more sensitive to filters in far. As abundant visual information is put into the near model, filters in near are more sensitive than filters in self. While far_INSTRU has big distance to INSTRU, so the filters in the model trained on it (far) are more insensitive than the filters in self, filters in far only have a bigger mAP on 40% categories, as shown in Fig. 9 (a) and (b).

Second, fine-tuning make the filters more sensitive to the target dataset. For 51% of the categories in INSTRU, the filters in the model trained on near_INSTRU (near) have a bigger mAP compared with filters in the model trained on INSTRU (self). While after fine-tuning, the filters in near have a bigger mAP than filters in self on 61% of the categories, as shown in Fig. 9 (a). Meanwhile, Fig. 9 (d) shows that filters after fine-tuning have bigger mAP compared with filters before fine-tuning on most of the categories on both near (75%) and far (76%).

At last, the sensitivity difference between near and far is big, as they are optimized on different dataset focusing on different visual patterns. After fine-tuning, they both fire on the target images, so the difference between them decreases. As shown in Fig. 9 (c), after fine-tuning, filter in near have big mAP only on 53% categories.

4.3.2 The discrimination of different layers. It is valuable to measure the discrimination of different layer features extracted from different models, as low layer features are common for all images and high layer features are specific to the task [60]. We analyze the classification accuracy of features extracted from layer conv1 to layer fc8 on different models on the dataset of INSTRU. Here conv1 represents the activation of the first convolutional layer followed with the Relu, Pooling and Norm, with a dimension of $96 \times 27 \times 27$. Conv2 and conv5 are the same situations. We use a logistic regression classifier composed with a fully-connected layer of 100 units and a softmax layer with all training examples exposed to the training procedure. The results are shown in Fig. 10. Many novel conclusions can be obtained.

First, the generalization capability of the activations of a pre-trained CNN model increases with the growth of the layer. What is more, if we transfer the features from a model which is trained on a source dataset which is different with the one we evaluate the performance (i.e., the target dataset), the activations of fc7 are the best. But if we train or fine-tune the model on the dataset itself, the activations of fc8 (which have smaller dimensions) are the best. As shown in the solid lines of Fig. 10 (a), the features of fc8 (66.62%, 60.86%, 53.74 respectively) obtain higher performance compared with the features of fc7 (66.12%, 59.08%, 53.32% respectively). However, the features of fc8 (57.78%, 44.64% respectively) obtain lower performance in all dash lines.

Second, for models trained on datasets that have different distances to target dataset, the performance of the near one is much higher than the performance of the far one. The case is always true for all the layers. What is more, fine-tuning from these models, the trend is still remained. This is corresponded with the conclusion that the more similar between the source and target datasets, the better performance fine-tuning obtains.



Fig. 10. The performance on INSTRU. (a) The discrimination of different layers when the features extracted from different models. Self represents the features extracted from the model which is trained on the 100 categories dataset of INSTRU. Near and Far represent the model trained on the 500 categories in dataset near_INSTRU and far_INSTRU respectively. FT-near indicates fine-tuning the model pre-trained on near_INSTRU on the target dataset, so does FT-far. (b) The left illustrates gain of the performance that the near model surpasses than the far one for each layer. The right illustrates gain of the performance that after fine-tuning surpasses before fine-tuning for the near and far models respectively.

Third, the gain of the performance that the near model surpasses than the far one decreases after fine-tuning, as shown in the left of Fig. 10 (b). The filters optimized on the dataset which is near to the target dataset are sensitive to the images in the target dataset, while filters optimized on the far dataset seem insensitive, so the difference between these two sets of filters is big. After fine-tuning on the target dataset, filters in these models both fire on the target images, so the difference decreases.



Fig. 11. The visualization of class images for different models. For each set, the first column shows same original images, and the second column is the corresponding class image computed from the model fine-tuned on near_INSTRU (FT-near). The third column is the corresponding image computed from the model fine-tuned on far_INSTRU (FT-far). The results show that class images computed from FT-near are better in representing the corresponding classes than the class images computed from FT-far (Best viewed in color).

Fourth, we compare the performance of pre-trained models with the one trained from scratch. Examples in the near source dataset have many common attributes or high level visual patterns with the ones in the target dataset also have. Meanwhile, the source dataset has bigger training examples $(500 \times 1300 = 650000)$ than the training examples in the target dataset $(100 \times 1300 = 130000)$, so representations extracted from the model trained on the near source dataset (Near) are better than the features extracted from the model trained on the target dataset itself (Self). However, examples in the far source dataset have less common high level visual patterns, so features extracted from the far model (Far) are inferior to the features extracted from Self. However, the performance of Far in the layers bellow conv5 is better than the performance of Self, as illustrated in Fig. 10 (a). The reason is that features in the low layers are common patterns for general object recognition, which have little relationship with the specific target task. With more training examples fed to Far, the model captures more simple visual patterns, leading a better performance.

4.3.3 Qualitatively analysis. We also qualitatively analyze the difference between different models. For a learned model, we utilize the method introduced by [45] to visualize the class images. More formally, let $S_c(I)$ be the score of the class c, which is computed by the classification layer of the model for image I. We would like to find the image I_c , such that the score S_c is high. So I_c can be regarded as the the notion of class c. Fig. 11 qualitatively shows some examples.

We can see that the fine-tuned near model (FT-near) learns more details of the classes in INSTRU, compared with the fine-tuned far model (FT-far). For example, as shown in the first set Fig. 11, FT-far only focuses on the balls of a *dumbbell*. In comparison, FT-near not only focuses on the balls but also the short bar which serves as a handle. All of the examples show that the class images computed from FT-near are more representative than the ones computed from FT-far. The results demonstrate that the learned features in FT-near are better in representating images in INSTRU. Manuscript submitted to ACM



Fig. 12. The effect of number of categories and training samples per category in the target dataset on the performance of fine-tuning. The horizontal lines in (c) represent that the models do not converge. (e) shows the comparison of two models when the number of categories in the target dataset is 100 (N = 100). For example, "near vs scratch" shows the gains of fine-tuning the model which is pre-trained on near_INSTRU (near) versus training the model from scratch (scratch) with the training samples per category varying from 1200 to 30. (f) shows the results under the settings of N = 80.

4.4 The Number of Categories and Training Examples per Category in the Target Dataset

The number of categories and training samples per category play an important role in training a convolutinal neural network. In this section, we analyze the effect of these two factors in the target dataset when conducting fine-tuning. As the average training examples for each category in ImageNet are almost 1200, we fine-tune the pre-trained models on target datasets with the training samples per category varying from 1200 to 30. At the same time, we also select 100, Manuscript submitted to ACM

80, 40, 20, 10 as the number of categories in the target datasets respectively. We use the models trained on far_INSTRU and near_INSTRU (introduced in Section 4.3) as two pre-trained models and select target datsets with different settings from INSTRU.

As illustrated in Fig. 12, the results suggest that with the decrease of the categories in the target datasets, the performance of fine-tuning from a pre-trained increases. It is true both with the far and near models as well as training from scratch. With the number of categories decrease, the accuracy may decrease as less training examples are fed to the network, which could more likely tend to overfiting. But the results illustrate that the accuracy is higher, because the the classification problem goes easier with less categories, which has less chances to make mistakes. It is important to note that when the data is too scarce to train a model, as shown in Fig. 12 (c), fine-tuning a pre-trained model on such a small dataset can also get significant performance, but training from scratch does not converge. The second conclusion we can obtain is that when the number of categories in the target dataset is fixed, the accuracy gets higher when more training examples are exposed to the model. The results show that more training examples can give better performance. The third conclusion is that the gain (i.e., near vs scratch, far vs scratch) decreases with the increase of training examples. The trend is the same for the gain of near versus far, as illustrated in Fig. 12 (e) and (f). With more training examples, the parameters in different models both are adjusted to fit the target data, being more sensitive to the images in the target dataset, so the difference decreases.

4.5 Fine-tuning to Deep or Shallow Layers

Features in low layers of convolutional neural networks are general image representations such as common edges, shapes and textures, while features in high layers are specific image representations for the target task. So when we fine-tune a pre-trained model on the target dataset, the parameters of the model in which layer should be fixed, and which layer should be retrained? The work of Yosinki [58] has suggested that fine-tuning all the layers can obtain significant performance, while fixed the parameters of some layers will bring about the problems of co-adaptation (for middle layers) and representation specificity (for high layers). Their work provides a sufficient analysis of fine-tuning when the training examples are abundant. But what are the results when the training examples are limited? In this section, we investigate the problem of fine-tuning to deep or shallow layers in a systematic way on the condition of limited training data.

In this section, we also use the models trained on far_INSTRU and near_INSTRU (introduced in Section 4.3) as two pre-trained models (denoted as near and far respectively). For the target dataset, we use all the categories in INSTRU, but only sample 240 examples per category for training (the original training examples per category is about 1200). In the experiments, the first *n* (from 1 to 7) layers of the network are frozen. For example, when n = 3, the parameters for the layers conv1, conv2 and conv3 are fixed during fine-tuning. The results are shown in Fig. 13. The first conclusion we can get is that it is better to fine-tune all the layers on the target dataset. This is consistent with the conclusion in [58] where the training examples in the target dataset is large. The second conclusion is that there is less co-adaptation (i.e., features that interact with each other in a complex or fragile way such that this co-adaptation could not be relearned by the upper layers alone [58]) in the model which is fine-tuned from near, compared to the model which is fine-tuned from far. Because the parameters in near is already fitted to the target data very well. They can be easily transferred to classifying the target data. It also can be concluded that just fine-tuning the high layers such as conv5, fc6 and fc7 can yield a satisfactory results, when the training data is small.



Fig. 13. The performance of fine-tuning to deep or shallow layers on different models when the training data is limited. Red and blue lines represent fine-tuning from the near model and the far model respectively.

4.6 The Effect of Data Augmentation

Data augmentation is a common and simple approach to learning discriminative and representative features by augmenting the training set with transformed versions of the original images. Techniques such as such as cropping, rotating, scaling, and flipping original input images have been widely used for image classification. In this section, we evaluate the effect of data augmentation for fine-tuning. We artificially constrain our access to the target training data, and evaluate the gain in recognition accuracy which is brought by data augmentation.

For the target datasets, we use all the categories in INSTRU, with the original training samples per category varying from 1200 to 30. Two pre-trained models (introduced in Section 4.3, denoted as near and far) are fine-tuned on these datasets respectively. As the original training examples per category is about 1200, we set 1200 as the upper bound. In our experiments, if the original number of images per category in the training set is smaller than 1200, we use the data augmentation technique in [40] to augment the training images to 1200.

The results are shown in Fig. 14. We compare the gain in accuracy when training network from scratch, fine-tuning network from the near model and the far model respectively. The conclusion is that data augmentation brings significant gains for training neural networks from scratch. While for fine-tuning, the gains are smaller. The performance for fine-tuning with and without data augmentation is almost the same. For training models from scratch, as models trained with small data do not generalize well, data augmentation increases the amount of training data, enhancing the ability to correctly classify images. However, a pre-trained model is initialized with proper weights. Fine-tuning it on the generated examples brings small changes. So data augmentation for fine-tuning is less effective than data augmentation for training networks from scratch.



Fig. 14. The comparison of data augmentation for fine-tuning and training models from scratch. For original number of images that is smaller than 1200, we increase the training examples to 1200 by data augmentation. For the left figure, red lines represent training network from scratch. Blue and green lines represent fine-tuning network from the near model and the far model respectively. The right figure shows the gain which is brought by data augmentation (Best viewed in color).

5 CONCLUSION

Features extracted from CNNs trained on large scale datassets are becoming common and preferred image representations for more and more visual tasks. Fine-tuning on a pre-trained model not only saves lots of time to avoid training networks from scratch, but also guarantees better performance. Our paper is dedicated to analyzing the factors that influence the performance of fine-tuning. We constrain our access to the subsets extracted from ImageNet, and explore each factor in turn. Many observations can be concluded from the results. First, with roughly the same distance to the target dataset, the bigger of the number of categories in the source dataset, the better performance fine-tuning obtains. Second, when the source dataset is fixed, the performance of fine-tuning increases with more training examples exposed to the retraining of the pre-trained model. What is more, the gain of fine-tuning versus training network from scratch decreases with the increase of retraining examples. Third, the more similar between the source and target datasets, the better performance fine-tuning obtains. We analyze the characteristic of different models at both filter-level and layer-level, and show their sensitivities to the target dataset. These conclusions provide useful and evidence-backed intuitions about how to implement fine-tuning for other visual tasks. In future work, we will explore architectures with an auxiliary loss to leverage the relationship between the source and target datasets explicitly when conducting fine-tuning.

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