An Efficient Source Model Selection Framework in Model Databases

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Abstract—With the explosive increase of big data, training a Machine Learning (ML) model becomes a computation-intensive workload, which would take days or even weeks. Thus, reusing an already trained model has received attention, which is called transfer learning. Transfer learning avoids training a new model from scratch by transferring knowledge from a source task to a target task. Existing transfer learning methods mostly focus on how to improve the performance of the target task through a specific source model, and assume that the source model is given. Although many source models are available, it is difficult for data scientists to select the best source model for the target task manually. Hence, how to efficiently select a suitable source model in a model database for model reuse is an interesting but unsolved problem.

In this paper, we propose SMS, an effective, efficient, and flexible source model selection framework. SMS is effective even when the source and target datasets have significantly different data labels, and is flexible to support source models with any type of structure, and is efficient to avoid any training process. For each source model, SMS first vectorizes the samples in the target dataset into soft labels by directly applying this model to the target dataset, then uses Gaussian distributions to fit for clusters of soft labels, and finally measures the distinguishing ability of the source model using Gaussian mixture-based metric. Moreover, we present an improved SMS (I-SMS), which decreases the output number of the source model. I-SMS can significantly reduce the selection time while retaining the selection performance of SMS. Extensive experiments on a range of practical model reuse workloads demonstrate the effectiveness and efficiency of SMS.

Index Terms—Source model selection, Transfer learning, Model Database

I. INTRODUCTION

Machine Learning (ML) has achieved incredible success in many complex data-driven applications, such as database [11], [21], [48], data mining [38], [43], and natural language processing [19], [31], to name but a few. In order to reduce the dependence of training data and the training time, model reuse (i.e., transfer learning) can be utilized to achieve higher performance (e.g., high accuracy, low loss), especially when the dataset is insufficient or the data quality is not high enough [34]. Transfer learning aims to transfer knowledge from a source task to a target task. Usually, transfer learning uses the source model (i.e., a previously trained model with a specific model structure) as the initial parameter and retrain this model on the target dataset. Most of the existing transfer learning methods [9], [26], [33], [54] assume that the source model is given. If there exist more than one previously trained models, data scientists need to manually search for the appropriate model as the source model for transfer learning [11], [29], [30], [39]. However, many source models are available in real-life applications, and thus, it is difficult and unreliable to select a suitable one manually [11], [39].

A bad source model may incur low performance after being retrained via transfer learning [5], [31], [46], [47], and may even inversely hurt the target performance (i.e., negative transfer [5], [46]). Besides, with the high demand for AI models in commercial products, companies may store each trained source model for every task in a model database. In addition, many one-stop AI open cloud platforms (e.g., Azure ML†, Cloud AutoML‡) are developed by big companies (e.g., Google, Microsoft, Hikvision), which provide one-stop training service for the dataset given by a user. These platforms often use transfer learning to improve the final model performance. Hence, the platform can store every trained model in a model database, and then, for a new training request raised by a user, it needs to select an appropriate source model in this database to obtain high performance via transfer learning.

Real-life Example. Consider the example shown in Fig. 1. Alice gets an image classification task on a newly collected image dataset, and chooses the ResNet-50 model to perform this task. Instead of training a ResNet-50 model from scratch for this task, transfer learning can be utilized to obtain higher image classification accuracy. In real-life applications, as the ResNet-50 model is a popular model, it has been trained for various tasks (e.g., image classification, object detection, etc.) on different datasets. All the previously trained models are stored in the model database, and can be used as source models for a new task. In order to select the best source model in the

†https://azure.microsoft.com/services/machine-learning
‡https://cloud.google.com/automl
model database for a new task, a naive solution is to evaluate each source model via transfer learning and then find the one with the highest accuracy. Although transfer learning can avoid training from scratch to reduce the training cost, the training cost is still high. Motivated by this, we aim to efficiently find the best source model in the model database for a new task.

Since AI models are the input of our problem, we focus on querying the model database instead of designing a specific model, which is a data management support for AI. Note that, the source dataset is not required, and it is usually not available due to many reasons (e.g., privacy protection). In order to efficiently select appropriate source models, we design a metric to rank the source models and select the best one, where three challenges exist.

**Challenge I:** How to design an effective metric, especially when the source labels and the target labels are greatly different? It is common to transfer knowledge from a model trained on a dataset that is greatly different from the target dataset in transfer learning [8], [18], [33], [46]. Back to the real-world example, source models are usually from very different domains. For instance, due to small data and expensive labeling for medical image datasets, the models trained on traditional image datasets (e.g., ImageNet-2012 dataset) is widely used in medical image classification task and can achieve higher performance than training from scratch [18], [46]. In this scenario, labels (e.g., goldfish, ostrich, baseball, etc.) of the source dataset (i.e., ImageNet-2012) are quite different from those (e.g., choroidal neovascularization, diabetic macular edema, etc.) of the target dataset (i.e., a medical image dataset), which makes it difficult to select suitable source models for the target task. Existing source model selection framework [44] tries to build a bridge between source labels and target labels via online information sources. Nonetheless, it cannot deal with the situation that source labels and target labels are significantly different. Hence, we aim to establish the relationship between the source model and the target dataset rather than between source labels and target labels.

**Challenge II:** How to design a general metric to support flexible source model selection? Many types of model structures (CNN, RNN, SVM, etc.) and machine learning tasks (image classification, text classification, regression, etc.) exist, which makes it difficult to select the appropriate source model of any type. For example, Alice wants to select appropriate source models of ResNet for an image classification task, while Bob wants to select appropriate source models of LSTM-RNN for a text classification task. However, previous studies are designed for specific models or tasks. SSFTL [44] can be used to select the source model only for the text classification task, and the CNN automatic source model selection framework [1] is mainly used for CNN models. To this end, we aim to develop a general source model selection framework that is able to support flexible model structures and various machine learning tasks.

**Challenge III:** How to efficiently select source models? The model training process of machine learning (especially deep learning) is time-consuming. As an example, it needs nearly two days to train a ResNet-50 model 100 epochs on ImageNet-2012 dataset using a 2080Ti GPU. If only a few candidate source models exist, we can retrain each source model on the target dataset in order to select the best source model with the highest accuracy. However, when the number of models grows to hundreds or even more, the cost of retraining each model is too high. Although the previous work [1] tries to reduce the training time, it still needs a training process, which is not efficient enough. In view of this, we aim to develop a method to estimate which source model may lead to the highest accuracy without any training process.

We propose SMS, an efficient source model selection framework. SMS measures the task-related knowledge of the source model and selects the source model with the most task-related knowledge. Specifically, we directly apply the source model on the target dataset without retraining, which outputs the soft label for each sample in the target dataset. The soft label is a probability vector to indicate the probability of being each class. We use the Gaussian distribution to fit for the soft label distribution of each class, based on which the separation degree of Gaussian distributions is introduced as the metric to rank the source models and select the best one.

We assume that the separation degree is positively correlated with the performance of the source model on the target task after retraining. Our assumption is based on an intuition commonly used in machine learning [1], [42], i.e., a good feature extractor with more knowledge for a specific dataset can well distinguish different classes of samples in the dataset after feature extraction. Fig. 2 shows the low distinguishing ability of source model $M_{S_1}$ and the high distinguishing ability of source model $M_{S_2}$. Two classes of soft labels predicted by $M_{S_1}$ are mixed together due to the low distinguishing ability of $M_{S_1}$, and two classes of soft labels predicted by $M_{S_2}$ are separated clearly due to high distinguishing ability. To sum up, i) since the soft labels can well capture the distinguishing ability of each source model on the target dataset, even when the source dataset is greatly different from the target dataset, the metric is effective; ii) our metric computation avoids high retraining cost, and thus, it is efficient; iii) our metric does not rely on the model structure, and hence, it is general to support various AI models. In addition, as the dimension of the soft label could be high, we use dimension reduction to
further improve the efficiency of our model selection method. The key contributions are summarized as follows:

- **Efficient source model selection framework.** We present an efficient source model selection framework SMS for model reuse. To the best of our knowledge, SMS is the first general framework to select appropriate source models without any training process. SMS is able to i) support the cases when the source dataset is greatly different from the target dataset; ii) support any type of AI model; and iii) offer efficient computation.

- **Distinguishing-based metric.** We use the source model to embed samples in the target dataset into soft labels, based on which, we design a Gaussian mixture-based metric to evaluate the distinguishing ability of the source model on the target dataset.

- **Improved SMS framework.** We propose an improved SMS, i.e., I-SMS, which utilizes an effective dimension reduction method to reduce the model selection time, and meanwhile, select high-quality source models.

- **Extensive experiments.** We conduct extensive experiments on six public datasets to verify the effectiveness and efficiency of the proposed approaches on a range of practical model reuse workloads.

The rest of the paper is organized as follows. Section II reviews the related work. Section III presents basic preliminary materials related to the source model selection and defines the problem of source model selection. Section IV details the proposed framework. Section V presents our experimental results. Finally, we conclude this paper in Section VI.

## II. RELATED WORK

In this section, we review the related work about model reuse and source model selection.

### A. Model Reuse

Many existing efforts have been devoted to model reuse, which is called transfer learning [34]. Knowledge distillation [3], [14] utilizes soft label and model transfer to compress the model and maintain the knowledge from the source model. Yosinski et al. [47] evaluated transferability of different layers in pre-training CNN models through comprehensive experiments, and they found that the bottom layers of CNN have better transferability while the top layers are more related to specific tasks. Mou et al. [31] analyzed the transferability of each layer in RNN. Hasani et al. [12] leveraged model reuse concept to merge previously constructed models for new queries. Zhang et al. [49] proposed EDDE, which transfers knowledge from a pre-trained network to accelerate the training process of ensemble learning. Neyshabur et al. [33] found that the low-level statistics lead to significant benefits of transfer learning, even if the source domain and the target domain are visually different.

Our source model selection problem is orthogonal to the above methods. The above methods assume that the source model is given, while we aim to select the suitable source model among a large number of candidate models for transfer learning. Note that, selecting a suitable source model can also improve the quality of model reuse in the target task.

### B. Source Model Selection

Although many efforts have been devoted to transfer learning, little work focuses on how to efficiently select source models for model reuse. To this day, the commonly-used source model selection method is still a manual effort. Nonetheless, the manual selection is time-consuming and ineffective especially when there are a large number of similar source model candidates.

Several methods are developed to support efficient source model selection. Miao et al. [29] proposed a model discovery method based on information retrieval. It relies on the description information (e.g., README) uploaded by users. Xiang et al. [44] utilize context information from WWW or Wikipedia to build a bridge between the source domain and the target domain to complete the transfer of knowledge. However, this method still cannot support the situation when the source labels and the target labels are completely different. Recently, Afridi et al. [11] presented a model selection framework based on information theory, which selects source models via part of training process. Nevertheless, this framework is still time-consuming due to the training process. In addition, the framework can only be applied to specific types of models, because it relies on the operation of the network structure. More recently, Sigl [39] provided a method of selecting the appropriate model based on the similarity between source dataset and target dataset, which avoids model training. Nonetheless, it requires the uploading of the source training datasets, which limits its applicability in real-life applications due to the data privacy issues.

In contrast, our SMS can support efficient source model selection even when the source labels and target labels are significantly different, and it is flexible to select source models of any architecture without any training process.

## III. PROBLEM STATEMENT

In this section, we present basic preliminary materials related to the source model selection for model reuse. A source model $M_{s_i}$ is a model trained on a source dataset $D_{s_i}$. A candidate set $S$ contains source models (i.e., $M_{s_1}, ..., M_{s_n}$) trained on different source datasets (i.e., $D_{s_1}, ..., D_{s_n}$).

**Retraining.** In real-world applications, a target dataset $D_t$ is always divided into a training set $D_{t_{train}}$ and a test set $D_{t_{test}}$. Given a source model $M_{s_i}$ and a target dataset $D_t = \{D_{t_{train}}, D_{t_{test}}\}$, retraining means that we use $M_{s_i}$ as the initial parameters and train $M_{s_i}$ on $D_{t_{train}}$ to get the final model $M_{i_{(s,t)}}$.

**Performance.** Given a source model $M_{s_i}$ and a target dataset $D_t = \{D_{t_{train}}, D_{t_{test}}\}$, the performance of $M_{s_i}$ after retraining is the result quality (e.g., accuracy, loss) of the final model $M_{i_{(s,t)}}$ on $D_{t_{test}}$.

Based on the concepts of retraining and performance, we provide the definition of source model selection.

**Definition 1:** (Source Model Selection) Given a source model candidate set $S = \{M_{s_1}, ..., M_{s_n}\}$ and a target dataset
**IV. THE PROPOSED SMS**

In this section, we describe the proposed SMS, an efficient Source Model Selection framework for model reuse. We first provide an overview of the SMS framework, and then we present the detailed methods.

**A. Overview**

Figure 3 depicts an overview of the SMS framework. SMS takes as inputs a candidate set \( S \) and a target dataset \( D_t \), and computes the ranking metric (i.e., the separation degree) of each source model on \( D_t \). Specifically, for each source model \( M_s \) in \( S \), the first stage of SMS directly apply \( M_s \) on the target dataset \( D_t \), and thus, all samples in \( D_t \) are transformed into vectors (i.e., soft labels) (to be detailed in Section 4.1). The second stage of SMS uses multivariate Gaussian distributions to fit for clusters of sample vectors (i.e., soft labels of different label types) (to be detailed in Section 4.2). The third stage of SMS computes the separation degree of \( M_s \) based on Gaussian distributions (to be detailed in Section 4.3). By comparing the separation degree of each source model, the appropriate source model will be selected.

The purpose of transfer learning is to use the knowledge possessed by the source model to assist the retraining, so that the final model has better performance after retraining on the target dataset than training from scratch, since the final model has both the knowledge from the source model and the knowledge from training on the target dataset. As a result, a source model with more target-related knowledge is likely to achieve higher performance after retraining. Therefore, we directly measure the target-related knowledge of the source model to rank the potential performance of source models without any training process. We use separation degree to measure the target-related knowledge, which is inspired by an intuition commonly used in machine learning [1], [42], i.e., a good feature extractor with more knowledge for a specific dataset can well distinguish different classes of samples in the dataset after feature extraction. The separation degree is defined to measure the ability of source models to distinguish different classes of samples. Hence, if a source model has a high separation degree on the target dataset, it is likely to have a large amount of target-related knowledge before retraining, making it easy to have more target-related knowledge after being retrained on the target dataset and achieve higher performance. Thus, we assume that the separation degree is positively correlated with the performance of the source model on the target task after retraining.

**B. Vectorization**

We first vectorize all the training samples in the target dataset according to a source model \( M_s \). Specifically, given a source model \( M_s \) and a target dataset \( D_t = \{(x_l, y_l), l = 1, ..., N\} \), we directly use \( M_s \) to predict each sample \((x_l, y_l) \in D_t\) and get a probability vector, called the soft label. Here, \( x_l \) is the training data, \( y_l \) is the corresponding label of \( x_l \), and \( N \) is the number of samples in \( D_t \).

To be more specific, we predict each sample \( x_l \) using \( M_s \) to get the hidden representation vector \( Z = (z_1, ..., z_n) \) from the final layer. Next, \( Z \) is further normalized by the extended softmax function to get the final soft label \( x_l' \) as follows:

\[
x_l' = (\alpha_1, ..., \alpha_n), \quad \text{as} \quad \alpha_m = \frac{\exp (z_m/T)}{\sum_{j=1}^{n} \exp (z_j/T)} (1 \leq m \leq n).
\]  

(1)

Note that, a soft label is a vector that denotes the probability distribution over classes. In other words, the source model
gives a possible "label" for each sample in the target dataset. The dimensionality of the soft label is only related to the source model from which it is generated. Each dimension of soft labels corresponds to a class of the source model. For example, a source model trained to identify dogs and cats generates 2-dimensional soft labels. It may generate a soft label (0.9, 0.1) for a sample (e.g., a tiger picture), meaning that the tiger picture has 90% possibility of being a cat and 10% possibility of being a dog. Another source model trained to identify traffic lights generates 3-dimensional soft labels, where three dimensions denote different colors, respectively. It may generate a soft label (0.3, 0.5, 0.2) for the same sample.

As a result, soft labels generated for the same sample by the above two source models are completely different, both in terms of the number of dimensions and the meaning of each dimension. To sum up, it is difficult to develop a ML model with soft labels as input to predict the target label, as the training dataset cannot be constructed.

In addition, $T$ is a parameter in the extended softmax function. The extended softmax function becomes the normal softmax function when the parameter $T$ is set to $1$. The larger $T$ is, the smaller the difference among probabilities will be, i.e., a larger $T$ makes a softer probability distribution over classes [14]. For example, when $T$ is set to $1$, the soft label for a sample is $(0.09, 0.83, 0.08)$; and when $T$ is set to $5$, the soft label is $(0.29, 0.44, 0.27)$. We use the extended softmax function rather than the normal softmax function because a softer probability distribution from $T$ larger than $1$ produces better selection results, as confirmed in Section 5.2.5.

After embedding each sample $x_i$ into a soft label vector $x_i^l$, we delete one extra dimension in the soft label to avoid redundant computation. It leads to no information loss since the sum of elements in the soft label is $1.0$ (due to the normalization of the softmax function). Finally, we get the target label set $D^l = \{x_i, y_i\}, i = 1, \ldots, N$.

### C. Fitting

Next, we divide the soft labels $D^l$ into disjoint clusters. Assume that the number of label types in the target dataset $D_t$ is $m$. We can obtain $m$ clusters $\{C_1, \ldots, C_m\}$, where $C_1 \cup \cdots \cup C_m = D^l_t$, and each cluster $C_u(1 \leq u \leq m)$ contains soft labels belonging to one label type.

Our model selection is general, which targets various machine learning models and tasks. Hence, it is difficult to make specific assumptions about the data distribution of soft labels. Gaussian distribution is the most widely used distribution. According to the generalizations of central limit theorem [10], a considerable number of phenomena in nature produce a final distribution that is approximately normal. In addition, it is common to use the Gaussian distribution to model the soft label distribution of a cluster. Motivated by this, we assume that soft labels of each cluster follow Gaussian distribution, which is verified its effectiveness in our experiments (see Section 5.2.5). Multivariate dimensional Gaussian distribution is a generalization of the one-dimensional Gaussian distribution to higher dimensions, as a soft label is a vector with more than one dimension. For simplification, "multivariate" is omitted in the subsequent contents.

Thus, we first fit for each cluster $C_u$ in $\{C_1, \ldots, C_m\}$ using a multivariate dimensional Gaussian distribution $G_u$.

$$G_u(x) = \frac{\exp\left(-\frac{1}{2}(x - \mu_u)^T \Sigma_u^{-1}(x - \mu_u)\right)}{(2\pi)^{\frac{n}{2}}|\Sigma_u|^{\frac{1}{2}}}.$$ (2)

where $\Sigma_u$ denotes the covariance matrix of $C_u$, and $\mu_u$ represents the mean vector of $C_u$.

### D. Separation Degree Computation

In the sequel, we define the separation degree between two Gaussian distributions, based on which, we also define the separation degree of the source model.

**Definition 2: (Separation degree between two Gaussian distributions)** Given two multivariate dimensional Gaussian distributions $G_u(x)$ and $G_v(x)$ fitted by two clusters $C_u$ and $C_v$. The peak of $G_u(x)$ and $G_v(x)$ are $P_u = G_u(\mu_u)$ and $P_v = G_v(\mu_v)$, respectively. A mixture of Gaussian distribution $F(x) = G_u(x) + G_v(x)$. The separation degree between $G_u(x)$ and $G_v(x)$ is defined as:

$$SD_{u,v} = SD_{v,u} = \frac{P_u}{F(\mu_u)} + \frac{P_v}{F(\mu_v)} - 1.$$ (3)

Here, $D_{u,v} \in [0, 1]$. The larger $D_{u,v}$ is, the more separated between two Gaussian distributions $G_u(\cdot)$ and $G_v(\cdot)$. After changing the form, and set

$$e_u(x) = \exp\left(-\frac{1}{2}(x - \mu_u)^T \Sigma_u^{-1}(x - \mu_u)\right),$$ (4)

the formula of separation degree can be obtained as follows:

$$\frac{\sqrt{|\Sigma_u|}}{\sqrt{|\Sigma_u|} + \sqrt{|\Sigma_v|e_u(\mu_u)}} + \frac{\sqrt{|\Sigma_v|}}{\sqrt{|\Sigma_v|e_v(\mu_v)} + \sqrt{|\Sigma_u|}} - 1.$$ (5)

The formula of separation degree after the form change can be computed more efficiently. Besides, the form of determination ($|\Sigma_u|$ and $|\Sigma_v|$) division can avoid the problem where the determination value is too large or too small to express.

Figure 4 illustrates three different cases for the separation degree between two Gaussian distributions. Here, $\mu_1$ and $\mu_2$ denote the mean value of $G_1(x)$ and $G_2(x)$, respectively. As $\mu_1$ is getting closer to $\mu_2$, $SD_{1,2}$ is changing from $1.0$ to $0.0$. Figure 4(a) shows the situation when $G_1(x)$ and $G_2(x)$ are...
Algorithm 1: Source Model Selection (SMS)

Input: A candidate set $S = \{M_{s_1},...,M_{s_n}\}$, a target dataset $D_t = \{(x_l,y_l), l = 1,...,N\}$, parameter $T$, integer $k$

Output: Top-$k$ appropriate source models

for each $M_{s_i}$ in $S$ do
  $C_{all} \leftarrow \emptyset$; // the list to store clusters
  $G_{all} \leftarrow \emptyset$; // the list to store Gaussian distributions
  $SD_{all} \leftarrow \emptyset$; // the list to store the separation degree between every two Gaussian distributions

for each $(x_i,y_i)$ in $D_t$ do
  use $M_{s_i}$ to predict $x_i$ and get the hidden representation vector $Z = (z_1,...,z_n)$ from the final layer;
  use the extended softmax function with parameter $T$ to normalize $Z$ and get the soft label $x_i^T$ // Eq. 1;
  delete the last dimension in the soft label $x_i$;
  $p \leftarrow y_i$;
  if $C_p$ not in $C_{all}$ then
    $C_p \leftarrow \emptyset$; // $C_p$ is the cluster of label $p$
    $C_{all} \leftarrow C_{all} \cup \{C_p\}$;
    get $C_p$ from $C_{all}$;
    $C_p \leftarrow C_p \cup \{x_i\}$;
    update $C_p$ in $C_{all}$;
  end if

for each cluster $C_p$ in $C_{all}$ do
  fit a multivariate dimensional Gaussian distribution $G_p$ to cluster $C_p$;
  $G_{all} \leftarrow G_{all} \cup \{G_p\}$;
end for

for each $G_p$ in $G_{all}$ do
  for each $G_q$ in $G_{all}$ do
    calculate the separation degree $SD_{(u,v)}$ between $G_p$ and $G_q$ // Eq. 5;
  end for
end for

calculate the separation degree $SD(M_{s_i},D_t)$ of source model $M_{s_i}$ by averaging $SD_{all}$ // Eq. 6;

return $k$ source models with $k$ highest separation degree

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far apart, in which $F(\mu_1) \approx G_1(\mu_1)$, $F(\mu_2) \approx G_1(\mu_2)$, and $SD_{(1,2)} = SD_{(2,1)} \approx 1.0$; Figure 4(b) depicts the situation when $G_1(x)$ and $G_2(x)$ are close, where $SD_{(1,2)} = SD_{(2,1)} = 0.5$; and Figure 4(c) plots the situation when $G_1(x)$ and $G_2(x)$ are the closest such that $\mu_1 = \mu_2$, in which $F(\mu_1) = F(\mu_2) = G_1(\mu_1) + G_2(\mu_2)$ and $SD_{(1,2)} = SD_{(2,1)} = 0.0$. The reason behind Definition 2 is that $G_u(\mu_u)/F(\mu_u) \in [0,1)$ and $G_v(\mu_v)/F(\mu_v) \in [0,1)$ are both monotonically decreasing when two separate $G_u$ and $G_v$ gradually approaches until their center points coincide ($\mu_u = \mu_v$).

As clusters are usually not highly related, we simply calculate the separation degree of source model using the average separation degree between any two Gaussian distributions.

**Definition 3:** (Separation degree of source model) Given a candidate set $S$, a target dataset $D_t$, and the number $m$ of label types in the target dataset $D_t$, the separation degree of source model $M_{s_i} \in S$ on $D_t$ is defined as:

$$SD(M_{s_i},D_t) = \frac{1}{m^2} \sum_{C_u \subseteq D_t} \sum_{C_v \subseteq D_t} SD_{(u,v)}. \quad (6)$$

We use the separation degree to rank the source models on the target dataset. The source model with the highest separation degree is the best model we select for the target task. The pseudo-code of source model selection is depicted in Algorithm 1. SMS takes a candidate set $S$, a target dataset $D_t$, a parameter $T$, and an integer $k$ as inputs, and outputs top-$k$ appropriate source models. Note that, each data sample in target dataset contains the real data $x_i$ and corresponding label $y_i$. For each source model $M_{s_i}$ in candidate set $S$, the algorithm first generates three lists to store clusters, Gaussian distributions and separation degrees separately (lines 1–4). After that, for each data sample $(x_i,y_i)$ in the target dataset, SMS uses $M_{s_i}$ to predict $x_i$ and get the hidden representation vector $Z = (z_1,...,z_n)$ from the final layer of $M_{s_i}$ (lines 5–6). Then, it uses the extended softmax function with parameter $T$ to normalize $Z$ to the soft label $x_i^T$ via Eq. 1, and delete the last dimension with no information loss (lines 7–8). Next, the algorithm puts the soft labels $x_i^T$ with the same labels $y_i$ into the same cluster (lines 9–15). Specifically, if the cluster $C_p$ of a particular label $p$ is not created, it initializes $C_p$ to empty and insert $C_p$ into $C_{all}$ (lines 9–12). In the sequel, for each cluster $C_u$, it fit a multivariate dimensional Gaussian distribution $G_u$ to $C_u$ and inserts $G_u$ into $G_{all}$ (lines 16–18). Then it calculates the separation degree $SD_{(u,v)}$ between every two Gaussian distributions via Eq. 5 and calculates the separation degree $SD(M_{s_i},D_t)$ of source model $M_{s_i}$ by averaging $SD_{all}$ via Eq. 6 (lines 19–22). Finally, $k$ source models with $k$ highest separation degree are returned (line 23).

E. Extend SMS to Regression Task

SMS is also flexible to support the regression task because SMS only ranks source models by computing the ability to distinguish different clusters of samples on the target dataset.

The separation degree of regression models is different from that of classification models because there is an additional relationship between samples and soft labels in regression models. Specifically, the samples whose labels are 0 are similar to the samples whose labels are 1, but far from the samples whose labels are 100. Here, sample labels are original data labels, which are different from soft labels. For example, a photo of a 100-year-old person is more like that of a 99-year-old person than that of a 20-year-old person. Therefore, to a certain extent, samples with similar labels are similar, while samples with dissimilar labels are quite different. Hence, SMS tries to use the weight $|u - v|^p$ to keep this relationship, where $u$ and $v$ are labels after discretized. By adding this weight, two Gaussian distributions with low separation degree in terms of their soft labels but far away in terms of their sample labels will be punished, which follows the rule of the regression model. We give the separation degree of source model definition for the regression task below.

**Definition 4:** (Separation degree of source model for the regression task) Given a candidate set $S$, a target dataset $D_t$, and a norm parameter $p \geq 0$, the separation degree of source model for the regression task $M_{s_i} \in S$ on $D_t$ is defined
as below:

$$SD (M_s, D_t) = \sum_{C_u \subseteq D_t} \sum_{C_v \subseteq D_t} |u - v|^p SD(u,v).$$  (7)$$

Note that, given two discretized class labels $u$ and $v$ in the target dataset $D_t$, if $u$ and $v$ are far from each other in the original continuous value, the weight $|u - v|^p$ would be large in order to emphasize the importance to distinguish $u$ and $v$.

### F. Improved SMS

Although SMS can efficiently select appropriate source models without any training process, it still needs to compute the separation degree of each source model, which contains two costly operations, i.e., the matrix determination and the matrix inverse in Eq. [5]. Let $n$ be the dimensionality of soft labels generated by a source model (i.e., the number of output units), the time complexities of the two operations are both $O(n^3)$, which is costly, especially when $n$ is large.

In order to alleviate this problem, we further propose the Improved SMS (I-SMS for short), which utilizes a dimension reduction method to cut down $n$. Specifically, I-SMS adds a fully connected layer with random parameters to the final output of the source model (without using the activation function), and the output dimension of the model is reduced to a lower dimension. Figure 5 illustrates the process of I-SMS. The source model is trained on ImageNet-2012 [36], which has 1,000 different classes. Thus, it is costly for SMS to compute the source model’s separation degree on the target dataset since there are 1,000 output units. In order to improve the efficiency, I-SMS adds a fully connected layer to the final output of the source model, and reduces the number of output units from 1,000 to 25. As discussed in Section V-B1, I-SMS can enhance the efficiency and scalability of SMS while retaining the source model selection performance.

Adding a fully connected layer can maintain the feature extraction capability of the source model, and thus, the performance of separation degree will not degrade severely. This can be explained mainly from two aspects. In the concept point of view, the deep learning model is composed of the first half of the network for feature extraction and the second half of the network for classification or other specific tasks. Adding a fully connected layer does not affect the feature extraction capability of the model. Therefore, the feature extraction ability (i.e., the target-related knowledge) of the source model can still be measured by the separation degree. In the calculation point of view, the fully connected layer is equivalent to linear transformation, and the linear transformation usually does not have a great influence on the distance relationship between points. For example, in a certain space, the distance between $A$ and $B$ is relatively small, and the distance between $A$ and $C$ is large. If three points ($A$, $B$, and $C$) use the same linear transformation, the distance between $A$ and $B$ is still relatively small with a high probability, and the distance between $A$ and $C$ is still relatively large with a high probability. Hence, the separation degree will not be greatly affected, and the performance will not degrade severely.

### V. EXPERIMENTS

In this section, we conduct extensive experiments to evaluate the effectiveness and efficiency of the proposed SMS and I-SMS compared with the state-of-the-art competitor.

#### A. Experimental Setup

**Datasets.** We use three types of tasks, i.e., image classification, text classification, and image regression. Six public datasets are used. Specifically, ImageNet-2012 [36] contains 1,331,167 images from 1,000 classes; CIFAR-10 [22] includes 60,000 images from 10 classes; FashionMNIST [45] contains 60,000 images from 10 classes; IMDB [27] contains 50,000 movie reviews from 2 classes; RCV1 [25] includes 65,385 news from 51 classes; and House Price [2] contains 2,140 images from 535 sample houses in California, USA. As shown in Table I based on six datasets, we support four cases.

| Case | Source Dataset | Target Dataset | Task Type        |
|------|----------------|----------------|------------------|
| Case 1 | ImageNet-2012 | ImageNet-2012 | Image Classification |
| Case 2 | FashionMNIST  | CIFAR-10       | Image Classification |
| Case 3 | IMDB           | RCV1           | Text Classification |
| Case 4 | CIFAR-10       | House Price    | Image Regression  |

Specifically, for **Case 1**, we divide ImageNet-2012 dataset into two sub-datasets for transfer learning. One sub-dataset $D_s$ contains 700 classes, and the other sub-dataset $D_t$ includes the rest 300 classes as target dataset. The label sets of $D_t$ and $D_s$ are $L_t$ and $L_s$, and $L_s \cap L_t = \emptyset$. We use $D_s$ to randomly generate 56 different sub-datasets, where the number of classes in each sub-dataset ranges from 2 to 200. In the training step, 56 source models of the same architecture ResNet-18 [13] are
trained on 56 sub-datasets, respectively, and 50-90% data of each sub-dataset is randomly used for training. We set the batch size to 512 and the number of training epochs to 20. In addition, ImageNet-2012 pre-trained model provided by PyTorch-torchvision[1] and the untrained ResNet-18 model are also considered as source model candidates. The output unit number of the two models is 1000 and 300, respectively. We use the above 58 source models as the candidate set. In the retraining step, we use the stochastic gradient descent with Nesterov momentum [32] for optimization and set the initial learning rate to 0.1, the momentum to 0.9, the batch size to 512, and the weight decay to $1 \times 10^{-4}$, and the learning rate is divided by 10 every 30 training epochs. We take Cross-entropy as the loss function. Besides, we use early stopping as the training stop condition, and if the loss of validation set does not decrease in 10 epochs, we shut down the retraining and take the model of the lowest loss. The number of output units in I-SMS is set to 25. Note that, we randomly divide the target dataset into three datasets, the first sub-dataset contains 80% data as training dataset, the second sub-dataset contains 10% data as validation dataset, and the third sub-dataset contains 10% data as test dataset. We use training dataset for retraining, validation dataset for early stopping, and test dataset for getting the actual performance (e.g. accuracy, loss). The parameter $T$ is set to 2.0 as default (to be discussed in Section 5.2.5).

For Case 2, we first randomly generate 200 different sub-datasets from FashionMNIST. The number of classes in each sub-dataset ranges from 2 to 5. In the training step, 200 models of LeNet-like CNN are trained on the 200 sub-datasets, respectively. 1-99% data of each sub-dataset is randomly used for training, and we set the batch size to 64 and the number of training epochs to 20. The above 200 trained models together constitute the candidate set. We take a subset of CIFAR-10 with four classes as the target dataset. In the retraining step, we use Adam [20], and set the base learning rate to $3 \times 10^{-4}$ and the batch size to 64. Besides, we use Cross-entropy as the loss function. Like Case 1, we also use early stopping.

For Case 3, in the training step, 50 source models of RNN with 128 hidden size and LSTM units [15] are trained on IMDB, respectively. 1-99% data of IMDB is randomly used for training, and we set the batch size to 64 and the number of training epochs to 20. We use the GloVe.6B.100d vectors as the pre-trained word embeddings. The above 50 source models constitute the candidate set. In the retraining step, we use Adam, and set the base learning rate to $5 \times 10^{-4}$ and the batch size to 128. The early stopping is also used.

For Case 4, we firstly generate 50 VGG-11 [40] network models on the subsets of the CIFAR-10 dataset, where the number of classes in each sub-dataset changes from 2 to 10, and 50-90% data of each sub-dataset is randomly used for training. The 50 trained source models constitute the candidate set. We take House Price dataset as the target dataset. In the retraining step, we use Adam, and set the base learning rate 10-9 to 0.001 and the batch size to 32. We take mean absolute percentage error [7] as the loss function and use the early stopping. In addition, we discretize the continuous labels into 10 discrete labels with the same number of samples.

**Competitor.** We compare the proposed SMS and I-SMS with existing CNN automatic source model selection framework (CAS) [1]. CAS is based on the principle of information theory, which is the first framework to study automatic model selection for transfer learning in convolutional neural networks. To the best of our knowledge, CAS is the only existing work that can automatically select models when source labels are quite different from the target labels.

**Evaluation metrics.** To evaluate the effectiveness of source model selection, we use three different metrics. (i) **Trendline.** Trendline is a visual representation of the correlation between the accuracy of the source model retrained on the target dataset and the ranking metric. Here, the ranking metric is the normalized separation degree for SMS (or I-SMS), while it is the normalized ranking score for CAS. Trendline is fitted by the least squares method. The greater the absolute value of the slope of the trendline, the better the performance of the source model selection framework is. (ii) **Pearson Correlation Coefficient (PCC).** PCC is utilized to measure the correlation coefficient between the accuracy of the source model retrained on the target dataset and the ranking metric precisely. The larger the PCC, the better the performance of the source model selection framework is. (iii) **Lowest Accuracy of Top-k Selected Source Models.** In order to measure the source model selection ability of the framework, we compare the lowest accuracy of the top-k source models selected by different frameworks on the target dataset.

To evaluate the efficiency of source model selection, we divide the running time in two parts, i.e., the predicting time and the other time. The predicting time corresponds to the cost where the frameworks predict the target sample, and output the hidden representation vectors on source models. The other time corresponds to the cost where the frameworks compute the transferability of the source models.

All experiments were implemented in Python 3.6.12 and PyTorch 1.6.0, and run on a Dell server with Ubuntu 18.04.5 LTS, Intel Xeon Silver 4210R 2.40GHz CPU, 128GB RAM, and GeForce RTX 2080Ti GPU.

| Datasets | Framework | PCC  | Time (h)        |
|----------|-----------|------|----------------|
| Case 1   | SMS       | 0.791| 2.347          |
|          | I-SMS     | 0.638| 0.648          |
|          | CAS       | 0.549| 0.830          |

\[^3]\text{https://pytorch.org/vision/stable/index.html}
1) Performance on ImageNet-2012: In the first set of experiments, we compare SMS and I-SMS with CAS using Case 1, where different subsets of ImageNet-2012 are used as source dataset and target dataset.

Figures 6(a)-6(c) plot the accuracy of each source model retrained on the target dataset w.r.t. the ranking metric. It is observed that all three frameworks, SMS, I-SMS, and CAS, can correctly rank the ImageNet-2012 pre-trained model as the top-1 model. This is because the accuracy of this model retrained on the target dataset is much higher than that of other source models. However, SMS and I-SMS can select the top-2 model correctly, while CAS selects a low-accuracy model as the top-2 model. In addition, the slope of the trendlines for SMS and I-SMS is larger than that for CAS. This implies that the correlation between the accuracy and the ranking metric in SMS and I-SMS is better than that in CAS. Figure 6(d) shows the lowest accuracy on the target dataset of top-2 source models. As observed, SMS and I-SMS can find better models than CAS when the performance of source models is close to each other. In addition, the performance of I-SMS is similar to that of SMS, which indicates that I-SMS can achieve good performance even when the output dimension of source models is reduced to 25.

Table III depicts the PCC and the running time of three different frameworks on Case 1. First, we can observe that the PCC of SMS and I-SMS is higher than that of CAS, which verifies the effectiveness of our methods. Second, all three different frameworks have the same predicting time, as they all predict each sample on the target dataset. However, SMS and I-SMS have fewer other time costs than CAS, which verifies the efficiency of our methods. As observed, I-SMS is much efficient than SMS as I-SMS further reduces the number of output units to improve efficiency. Note that the predicting time takes a high proportion of the total running time. The predicting time is linearly related to the number of samples, and thus, it can be reduced proportionally by sampling. Therefore, we can further reduce the running time of I-SMS by random sampling.

Next, we evaluate the robustness of I-SMS on random sampling. Figure 7(a) shows the PCC of I-SMS when the sampling rate of the target dataset varies from 0.025 to 0.8. It is observed that the PCC of I-SMS increases with the sampling rate. This is because I-SMS can better estimate the target-related knowledge of source model candidates as the sampling rate grows. To be more specific, Figure 7(b) depicts the accuracy of source models retrained on the target dataset w.r.t. the normalized separation degree in I-SMS when the sampling rate is 0.1. We can observe that I-SMS can select the top-2 models correctly and perform better than CAS (shown in Figure 6(c)). It confirms the robustness of I-SMS on random sampling over the target dataset. Thus, I-SMS can reduce the predicting time by the random sampling on the target dataset while retaining the source model selection performance.

Through the experiments on the large image classification dataset ImageNet-2012, we have verified that I-SMS can enhance the efficiency and scalability of SMS while maintaining the source model selection performance. For simplification, we omit I-SMS in the rest of the experiments due to similar experimental results.

2) Performance on Different Datasets: The prior work [33] has shown that transfer learning can improve the performance of the target task even if the source dataset is quite different from the target dataset. In this set of experiments, we compare SMS with CAS on both image and text classification tasks when the source dataset and the target dataset are different (i.e., using Cases 2 and 3).

Figures 8(a) and 8(b) show the accuracy of source models retrained on the target dataset for the image classification w.r.t. the ranking metric in SMS and CAS, respectively. Figures 8(c) and 8(d) depict the accuracy of source models retrained on the target dataset for the text classification w.r.t. the ranking metric. It is observed that all three frameworks, SMS, I-SMS, and CAS, can correctly rank the ImageNet-2012 pre-trained model as the top-1 model. This is because I-SMS can better estimate the target-related knowledge of source model candidates as the sampling rate grows. To be more specific, Figure 7(b) depicts the accuracy of source models retrained on the target dataset w.r.t. the normalized separation degree in I-SMS when the sampling rate is 0.1. We can observe that I-SMS can select the top-2 models correctly and perform better than CAS (shown in Figure 6(c)). It confirms the robustness of I-SMS on random sampling over the target dataset. Thus, I-SMS can reduce the predicting time by the random sampling on the target dataset while retaining the source model selection performance.

Through the experiments on the large image classification dataset ImageNet-2012, we have verified that I-SMS can enhance the efficiency and scalability of SMS while maintaining the source model selection performance. For simplification, we omit I-SMS in the rest of the experiments due to similar experimental results.

![Fig. 6. Ranking Results on ImageNet-2012](image)

![Fig. 7. Impact of Random Sampling on I-SMS](image)

| Table III | PERFORMANCE COMPARISON ON CASE 2 AND CASE 3 |
|-----------|--------------------------------------------|
| Dataset   | Framework | PCC | Time (min) | Predicting | Other |
| Case 2    | SMS       | 0.582 | 0.159 | 1.446 |
|           | CAS       | 0.032 | 1.648 |
| Case 3    | SMS       | 0.889 | 0.489 | 1.341 |
|           | CAS       | 0.526 | 2.680 |
metric in SMS and CAS, respectively. We can observe that the correlation (i.e., the slope of trendline) between the accuracy metric in SMS and CAS, respectively. We can observe that the metric in SMS is stronger than that in CAS for both image classification and text classification.

Figures 8(e) and 8(f) plot the lowest accuracy on the target dataset of the top-$k$ source models selected by SMS and CAS for the image classification and text classification, respectively. It is observed from Figure 8(e) that the lowest accuracy of SMS is firstly larger than that of CAS and then becomes comparable with that of CAS as $k$ grows. This is because the accuracy of candidate source models are close to each other, resulting in the performance degradation of SMS. Figure 8(f) shows that the lowest accuracy of SMS is stably larger than that of CAS with the growth of $k$. This implies that SMS can achieve better source model selection performance than CAS in both the image classification and text classification when the source dataset and the target dataset are greatly different.

Table II lists the PCC and the running time of SMS and CAS on the image classification (i.e., FashionMNIST to CIFAR-10 datasets) and text classification (i.e., IMDB to RCV1 datasets). As observed, SMS can get higher PCC and shorter running time than CAS, which again confirms the effectiveness and efficiency of SMS.

3) Performance on Regression Task: SMS is flexible to the regression task. In this set of experiments, we verify the performance of SMS on the regression task using Case 4.

Figure 9(a) shows the loss of source models retrained on the target dataset w.r.t. the normalized separation degree computed by SMS when the norm parameter $p = 2$. It is observed that SMS can correctly rank the top-2 models with the smallest loss after retraining on the target dataset. Besides, the slope of the trendline has a large absolute value. This validates the performance of SMS when it extends to the regression task. To further study the impact of $p$, we vary $p$ from 0 to 7. Figure 9(b) plots the highest loss on the target dataset w.r.t. the normalized separation degree computed by SMS. We observe that SMS can achieve better source model selection result when $p$ is 2, and with the increase of $p$, the results are getting worse. The reason is that when $p$ is too large, the SMS will pay too much attention to the clusters with distant labels, and nearly completely ignore the clusters with closer labels, which is also wrong and harmful to the ranking results. Thus, it is better to set $p$ to 2 in practice.

4) Comparison with the method using meta-data: In this set of experiments, we explore the effect of using data distribution (one type of meta-data) to find the best (i.e., the closest) source model from the target data. We use Kullback–Leibler diver-
The experimental settings are the same as those used for the source dataset and the target dataset. It is difficult to use meta-data to consider all of the factors that determine whether the source model has useful knowledge for the target task, such as the way of training (epoch, learning rate, etc.) and dataset characteristics (similarity between source and target datasets, dataset size, data quality, etc.). It is observed that PCC achieves the highest value when $T$ is set around 2.0 in all three cases. Second, the PCC values are high over most of the $T$ values if $T$ is neither too small (e.g., 0.5) or too big (e.g., 32), which indicates the robustness of SMS over different $T$ values. Thus, we set $T$ to 2.0 as default.

6) Comparison with clustering evaluation metrics: We compare our separation degree with four popular clustering evaluation metrics, including the distance between centroids (DBC for short), the longest distance within cluster (LDWC for short), Davies–Bouldin index (DBI for short) and Calinski-Harabasz score (CH for short), using Cases 1-3 stated in Section 5.1.

Figure 12 shows the lowest accuracy of top-$k$ source models selected by SMS using the separation degree and four different clustering evaluation metrics. Here, due to the space limitation, we only show the lowest accuracy of top-$k$ source models. Note that LDWC metric calculation is time-consuming, especially when the target dataset is large. We omit the results for Cases 1 and 3 in Figures 12(a) and 12(c), as it can’t finish in 24 hours of computation. It is observed that the separation degree always performs the best. Actually, the separation degree can also be regarded as a clustering evaluation metric, as we use Gaussian distributions to model clusters of soft labels. The experimental results indicate the effectiveness of the separation degree on Gaussian distributions.

7) SMS with various model structures simultaneously: We further evaluate the robustness of SMS using 12 commonly-used CNN networks on the ImageNet-2012 dataset simultaneously, which includes ResNet-18 [13], ResNet-34, ResNet-50, Densenet121 [16], VGG-11 [40], VGG-13, VGG-16, VGG-19, Googlenet [41], Alexnet [23], Squeezenet1_0 [17], and Mobilenet_v2 [37]. The experimental settings are the same as Case 1 stated in Section 5.1. For each model structure, we train 6 source models on 6 sub-datasets, respectively. Thus, we generate 72 trained models with 12 different structures as candidates. Figure 13 plots the accuracy of each source model retrained on the target dataset w.r.t. normalized separation degree. It is observed that the correlation between our estimation metric and the actual performance is strong. SMS is able to select the best model with the highest accuracy on the target dataset, which confirms the robustness of SMS even for source models with different structures.

Figure 13 also shows that the scatter points are distributed
into two clusters, and the correlation between separation degree and accuracy is strong within each cluster. The accuracy of models in the lower cluster is lower than that in the upper cluster, even if models in the lower cluster have higher separation degree than some models in the upper cluster. This is because SMS selects the source model according to the separation degree, which measures the amount of knowledge of the source model related to the target task without retraining the model. The model with the large separation degree tends to have a large amount of knowledge after retraining in the target dataset, and thus, obtains good performance. However, the amount of knowledge after retraining is determined not only by the amount of knowledge of the source model, but also by the model structure. For example, an Alexnet source model has similar target-related knowledge as a ResNet-50 source model before being retrained. Nevertheless, the learning ability of the Alexnet model is lower than ResNet-50. Thus, Alexnet model can learn a limited amount of knowledge from the target dataset in the retraining process, resulting in lower final accuracy compared with the ResNet-50 source model.

To sum up, this set of experiments verifies the robustness of SMS to select appropriate source models with various model structures. It is better to use SMS for transfer learning when the model structure is determined.

VI. CONCLUSIONS

In this paper, we present an efficient source model selection framework SMS. SMS can efficiently select the source model from the candidate models in different tasks under different architectures for model reuse. Given a candidate model, SMS firstly utilizes soft labels to represent the samples in the target dataset and uses Gaussian distributions to fit clusters of soft labels. Then, SMS utilizes the separation degree to measure the distinguishing ability of the candidate model on the target task. In addition, an improved SMS is proposed to reduce the selection time while retaining the performance. Finally, we conduct extensive experiments to verify the effectiveness and efficiency of the proposed SMS. In the future, it is of interest to study the factors including platform, deployment, and quality/explainability to further improve the quality of retraining the source model.

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