How to Pick the Best Source Data?
Measuring Transferability for Heterogeneous Domains

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Abstract

Given a set of source data with pre-trained classification models, how can we fast and accurately select the most useful source data to improve the performance of a target task? We address the problem of measuring transferability for heterogeneous domains, where the source and the target data have different feature spaces and distributions. We propose TRANSME, a novel method to efficiently and accurately measure transferability of two datasets. TRANSME utilizes a pre-trained source classifier and a reconstruction loss to increase its efficiency and performance. Furthermore, TRANSME uses feature transformation layers, label-wise discriminators, and a mean distance loss to learn common representations for source and target domains. As a result, TRANSME and its variant give the most accurate performance in measuring transferability, while giving comparable running times compared to those of competitors.

1 Introduction

Given a set of source data with pre-trained classification models, how can we fast and accurately select the most useful source data to improve the performance of a target task? In supervised learning, the amount of labeled data has a direct effect on the performance of the target task. However, labeling a sufficient amount of data is cost and time-intensive, and it is often impossible to get enough data when it comes to rare events or restricted data e.g., mechanical faults or personal information. For this reason, there have been growing interests in Transfer Learning which aims to transfer data or model from a source task to a target task, to reduce the demand of the target data. There are several flavors of transfer learning. In Homogeneous Transfer Learning [III, 2007; Yao and Doretto, 2010; Pan et al., 2010; Gong et al., 2012; Oquab et al., 2014], both source and target domain have an identical feature space. In Heterogeneous Transfer Learning [Shi et al., 2010; Kulis et al., 2011; Wang and Mahadevan, 2011; Duan et al., 2012b; Zhou et al., 2014; Li et al., 2014; Ye et al., 2018] which we focus on in this paper, two feature spaces have different dimensions.

The heterogeneous transfer learning enlarges the pool of available source data for transfer learning; however, it also introduces a significant challenge: the distribution as well as the meaning of the features of source and target domains are different. Such difference may lead to negative transfer, where the accuracy of the target task decreases after the transfer. Thus, it is important to quickly measure the transferability between a source data and a target data, such that we avoid transferring source data which lead to negative transfer.

In this paper, we propose TRANSME, a novel method to accurately and quickly measure the transferability between a source data and a target data. The base model of TRANSME consists of four modules: source encoder, decoder, label predictor, and domain classifier (see Figure 2). The source encoder maps the source data into the target’s feature space such that they have homogeneous representations. We feed the target data and the mapped source data into the same decoder and the label predictor to predict labels. We decrease the training time by reusing the pre-trained source model with fixed weights. The domain classifier forms an adversarial architecture with the source encoder to maximize the accuracy: the domain gap between the source and the target data is reduced by the competition between the domain classifier and the source encoder. This reduced domain gap enhances the accuracy of measuring the transferability. We improve the accuracy of the base model of TRANSME by three additional ideas: label-wise domain classifiers for better adversarial training, a reconstruction loss for enhancing the label prediction, and a mean distance loss for better learning the homogeneous representations. Extensive experiments show that TRANSME and its variant give the best accuracy, while giving comparable running times compared to those of competitors (see Figure 1).

The main contributions of this paper are as follows.

- **Problem Definition.** We define the problem of measuring the transferability between heterogeneous datasets. Unlike previous works that focus on fully transferring models, the problem focuses on measuring the transferability between datasets efficiently and accurately.
- **Method.** Our proposed method TRANSME uses a pre-trained source model and an adversarial architecture
to efficiently and accurately measure the transferability between two datasets. TRANSMETER learns homogeneous representations of source and target domains using feature transformation layers, label-wise discriminators, and a newly designed mean distance function.

- **Experiments.** Extensive experiments show that TRANSMETER and its variant give the best accuracy in measuring transferability, with similar running times compared to other methods.

The rest of the paper is organized as follows: related works in Section 2, proposed method in Section 3, experiments in Section 4, and conclusion in Section 5.

## 2 Related Works

We review previous works on heterogeneous domain adaptation, negative transfer, and measuring transferability.

### 2.1 Heterogeneous Domain Adaptation

Heterogeneous domain adaptation aims for transfer learning in heterogeneous domains. However, the different feature spaces and the distributions impose significant challenges. Recent studies to address the challenges are divided into two groups: symmetric and asymmetric feature-based transfer learning. Symmetric approaches transform both the source and the target domains into a common latent space [Shi et al., 2010; Duan et al., 2012b; Yan et al., 2017] while asymmetric approaches transform only the source domain to the target domain [Kulis et al., 2011; Zhou et al., 2014; Ye et al., 2018]. The base model of TRANSMETER can be regarded as an asymmetric feature-based transfer learning, but it also uses the idea of symmetrically transforming the target feature space to increase flexibility.

### 2.2 Negative Transfer

[Pan and Yang, 2010; Weiss et al., 2016] define negative transfer as "transferring knowledge from the source can have a negative impact on the target learner". The negative transfer comes from the difference between the source and the target data distributions, and was observed in various settings [Rosenstein et al., 2005; Duan et al., 2012a; Ge et al., 2014; Cao et al., 2018]. [Wang et al., 2018] observed that three main factors for negative transfer are algorithms for transfer learning, the divergence between joint distributions, and the size of the labeled target data.

### 2.3 Measuring Transferability

As the number of available source data gets larger, it becomes very important to exploit the source data to boost the performance of a target task. Then it is necessary to efficiently and accurately estimate the transferability between a source and a target data before a full transfer. [Shi et al., 2013] and [Seah et al., 2013] use the ratio of the clustered source data in the unified feature space, and the confidence of the pseudo-labeled target data, respectively, to remove the suspicious source data to avoid negative transfer. However, none of the previous works explicitly evaluate the transferability. Our proposed TRANSMETER explicitly measures the transferability and chooses the best data.

### Table 1: Symbol description.

| Symbol | Description |
|--------|-------------|
| $N$    | Number of given source tasks |
| $D_s$  | A set of $N$ source datasets |
| $H_s$  | A set of $N$ source classifiers |
| $x_{s(i)}$ | Input features of the $i$-th source data |
| $y_{s(i)}$ | Label of the $i$-th source data |
| $h_{s(i)}$ | Classifier of the $i$-th source data |
| $d_{s(i)}$ | Input dimension of the $i$-th source data |
| $x_t$  | Input features of the target data |
| $y_t$  | Label of the target data |
| $h_t$  | Classifier of the target data |
| $d_t$  | Input dimension of the target data |

Figure 1: Comparison of (a) the rank correlation and (b) the running time among TRANSMETER, TRANSMETER-M, and competitors. Note that TRANSMETER and TRANSMETER-M give the highest overall rank correlation while giving comparable running times compared to other methods.
3 Proposed Method

We formally define the problem and propose TRANSFER, our novel method for transferability measurement. Table 1 summarizes the symbols used.

3.1 Problem Definition

Given a set $D_s = \{(x_s^{(i)}, y_s^{(i)})\}_{i=1}^N$ of $N$ source datasets with classifiers $H_s = \{h_s^{(i)}\}_i$ and the target data $(x_t, y_t)$ where $x_s^{(i)} \in R^{d_s}$, $x_t \in R^{d_t}$, and $y_s^{(i)}, y_t \in \{0, 1\}$, our objective is to find the best source data and its related classifier that improves the target performance the most after transferring them to the target task. We focus on heterogeneous transfer learning where $d_s^{(i)} \neq d_t$.

3.2 Overview

We propose TRANSFER, a novel method to determine the most useful source data by measuring the transferability. Figure 2 depicts the overall structure of TRANSFER, which consists of three learnable networks: source encoder ($E_s$), decoder ($D$), and domain classifiers ($DC_0$ and $DC_1$). The label predictor (LP) denotes the pre-trained source model and is fixed while training. The source encoder generates the homogeneous representation ($x'_s$) by mapping the source input features $(x_s \in R^{d_s})$ into target feature space $(x_t \in R^{d_t})$. For the sake of utilizing the pre-trained source model where the input dimension of the model should be $d_s$, the decoder transforms the dimension of homogeneous representations ($x'_s$ and $x_t$) from $d_t$ to $d_s$. Similar to the Domain Adversarial Neural Networks [Ganin et al., 2017], the domain classifier (DC) distinguishes the source and the target domains, while the source encoder extracts the domain-invariant features. After training, the domain classifier will not be able to discriminate the two domains, and not be used in the inference step.

Algorithm 1 shows TRANSFER. Given a source data, a pre-trained source model with the source data, and a target data, the algorithm learns the model parameters $\theta_c$, $\theta_s$, $\theta_{0,dc}$ and $\theta_{1,dc}$ to measure transferability. Note that the input parameters $\theta_{lp}$ of the pre-trained source model are fixed. All the learned parameters are initialized with random values. In the training process, the source and the target data flow into the model simultaneously, and the parameters are updated using gradient descent.

3.3 Objective Function

We define our learning objective as follows:

$$L_{cn} = \alpha L_l - \lambda \beta L_d + \gamma L_r + \delta L_{md}$$

$$L_{dc} = \alpha L_l + \gamma L_r$$

$$L_{dc} = \beta L_d$$

Algorithm 1 TRANSFER

| Input: source labeled data $S = \{(x_{s,i}, y_{s,i})\}_{i=1}^n$, parameters $\theta_{lp}$ of the pre-trained source model, and target labeled data $T = \{(x_{t,j}, y_{t,j})\}_{j=1}^n$. |
| Output: learned parameters: $\theta_c$ of the source encoder $f_c$, $\theta_d$ of the decoder $f_d$, and $\theta_{0,dc}$ and $\theta_{1,dc}$ of the label-wise domain classifiers $f_{0,dc}$ and $f_{1,dc}$. |

1: initialize: $\theta_c, \theta_d, \theta_{0,dc}$, and $\theta_{1,dc}$ randomly
2: while stopping criterion is not met do
3:   $y_{s,i} \leftarrow \text{softmax}(f_{lp}(f_d(x_{s,i}; \theta_d); \theta_{lp}))$
4:   $y_{t,j} \leftarrow \text{softmax}(f_{lp}(f_d(x_{t,j}; \theta_d); \theta_{lp}))$
5:   $x_{t,s,t} \leftarrow f_d(x_{s,i}; \theta_d)$
6:   if label is 0 then
7:     $d_{0,s,i} \leftarrow \text{softmax}(f_{0,dc}(x_{s,i}; \theta_{0,dc}))$
8:     $d_{0,t,j} \leftarrow \text{softmax}(f_{0,dc}(x_{t,j}; \theta_{0,dc}))$
9:     $x_{0,s} \leftarrow f_d(x_{s,i}; \theta_d)$
10:    $x_{0,t} \leftarrow f_d(x_{t,j}; \theta_d)$
11: else
12:     $d_{1,s,t} \leftarrow \text{softmax}(f_{1,dc}(x_{s,i}; \theta_{1,dc}))$
13:     $d_{1,t,j} \leftarrow \text{softmax}(f_{1,dc}(x_{t,j}; \theta_{1,dc}))$
14:     $\hat{x}_{1,s} \leftarrow f_d(x_{s,i}; \theta_d)$
15:     $\hat{x}_{1,t} \leftarrow f_d(x_{t,j}; \theta_d)$
16: end if
17: compute $L_{cn}$, $L_{dc}$, and $L_{dc}$ according to the equations (1)-(8)
18: update parameters $\theta_c, \theta_d, \theta_{0,dc}$, and $\theta_{1,dc}$ using gradient descent
19: end while
\(L_{en}, L_{dc},\) and \(L_{dc}\) denote the loss functions for the parameters in the source encoder, the decoder, and the domain classifiers, respectively. \(L_{en}, L_{dc},\) and \(L_{dc}\) are constructed from four different loss functions: label predictor loss \(L_l,\) feature reconstruction loss \(L_r,\) domain discrimination loss \(L_d,\) and mean distance loss \(L_{md}\). \(\alpha, \beta, \gamma, \lambda\) and \(\delta\) are hyperparameters. In the following, we describe the four loss functions in detail.

**Label Predictor**

The label predictor loss \(L_l\) is designed to correctly classify instances.

\[
L_l = \frac{L_{l,s} + L_{l,t}}{n_s + n_t}
\]

\[
L_{l,s} = \sum_{i=1}^{n_s} -y_{s,i} \log(\hat{y}_{s,i}) - (1 - y_{s,i}) \log(1 - \hat{y}_{s,i})
\]

\[
L_{l,t} = \sum_{j=1}^{n_t} -y_{t,j} \log(\hat{y}_{t,j}) - (1 - y_{t,j}) \log(1 - \hat{y}_{t,j})
\]

\(y\) and \(\hat{y}\) denote the ground truth and the predicted label, respectively. \(L_{l,s}\) and \(L_{l,t}\) are summation of instance losses from the source and the target data, respectively. \(n_s\) and \(n_t\) are the numbers of source and target instances, respectively.

**Feature Reconstruction**

The feature reconstruction loss \(L_r\) is designed to recover the original source features to reuse the pretrained source model. This can be thought of as an autoencoder where the source encoder maps the source input features into a constrained code, and the decoder recovers the code to the input features. The model is trained to minimize the reconstruction error for each source data point.

\[
L_r = \frac{1}{n_s} \sum_{i=1}^{n_s} ||x_{s,i} - \hat{x}_{r,s,i}||^2
\]

\(x_{r,s,i}\) denotes the decoded features of the \(i\)th source instance.

**Label-wise Discrimination**

The domain discrimination loss \(L_d\) is designed to improve the accuracy of the label prediction while making the source and the target features indistinguishable. We separate instances for labels 0 and 1, and perform domain classification for each label. Such separation prevents all the source instances from being mapped close to target points of only a single label.

\[
L_{d} = \frac{L_{0,dc} + L_{1,dc}}{n_s + n_t}
\]

\[
L_{0,dc} = -\sum_{i=1}^{n_{0,s}} \log(1 - \hat{d}_{0,s,i}) - \sum_{j=1}^{n_{0,t}} \log(\hat{d}_{0,t,j})
\]

\[
L_{1,dc} = -\sum_{i=1}^{n_{1,s}} \log(1 - \hat{d}_{1,s,i}) - \sum_{j=1}^{n_{1,t}} \log(\hat{d}_{1,t,j})
\]

\(n_{0,s}, n_{1,s}, n_{0,t},\) and \(n_{1,t}\) represent the numbers of source and target instances with labels 0 and 1, respectively. \(\hat{d}_{0,s,i}\) and \(\hat{d}_{1,s,i}\) denote the predicted domain classes of the \(i\)th source instances with labels 0 and 1, respectively, while \(\hat{d}_{0,t,j}\) and \(\hat{d}_{1,t,j}\) denote those of the \(j\)th target instances with labels 0 and 1, respectively.

**Mean Distance**

The means distance loss \(L_{md}\) is designed to further make the source and the target data indistinguishable. For a batch of source and target instances, we minimize the distance between the average source vector and the average target vector in the homogeneous representation.

\[
L_{md} = L_{0,md} + L_{1,md}
\]

\[
L_{0,md} = ||m_{0,s} - m_{0,t}||^2
\]

\[
L_{1,md} = ||m_{1,s} - m_{1,t}||^2
\]

\(m_{0,s}, m_{0,t}, m_{1,s},\) and \(m_{1,t}\) are the mean vectors for each label and domain.

## 4 Experiments

We conduct experiments to answer the following questions on the performance and efficiency of TRANSmeter.

- **Q1.** Model sanity check (Section 4.2). Does TRANSmeter improve the accuracy of a target task?
- **Q2.** Ablation study (Section 4.3). Which variant of TRANSmeter provides the best accuracy?
- **Q3.** Comparison to competitors (Section 4.4). What are the results of comparison between TRANSmeter and competitors?

| Data                        | Abbreviation             | Field       | Features | Instances |
|-----------------------------|--------------------------|-------------|----------|-----------|
| Australian Credit Approval¹ | Australian              | Financial   | 14       | 690       |
| Breast Cancer Wisconsin (Diagnostic)¹ | Cancer-diag          | Health      | 32       | 569       |
| Breast Cancer Wisconsin (Original)¹ | Cancer-orig           | Health      | 10       | 699       |
| Student Grade Prediction¹   | Grade                   | Education   | 33       | 649       |
| HTRU2 Data Set¹             | Pulsar                  | Astronomy   | 8        | 17898     |

Table 2: Description of the Datasets.
| Symbol     | Description                                                                 |
|------------|-----------------------------------------------------------------------------|
| TRANS METER | Our proposed model                                                           |
| TRANS METER-0 | TRANS METER without any improvements                                       |
| TRANS METER-A | TRANS METER without reconstruction loss                                    |
| TRANS METER-L | TRANS METER without label-wise discriminators                                |
| TRANS METER-M | TRANS METER without mean distance loss                                       |

Table 3: Descriptions of TRANS METER and its four variants.

| Model         | Australian Accuracy | Cancer-diag Accuracy | Cancer-orig Accuracy |
|---------------|---------------------|----------------------|----------------------|
| TRANS METER   | 65.70               | 94.74                | 90.73                |
| TRANS METER-0 | 61.84               | 92.98                | 90.73                |
| TRANS METER-A | 65.70               | 94.74                | 90.73                |
| TRANS METER-L | 65.70               | 92.98                | 90.73                |
| TRANS METER-M | 62.80               | 94.74                | 90.73                |

Table 4: The result of the self-transfer. TRANS METER and its variants succeed in improving the accuracy (%) except for TRANS METER-0.

4.1 Experimental Settings

We introduce experimental settings including datasets, pre-trained models, and baseline methods. All of our experiments are done in a workstation with GeForce GTX 1080 Ti.

Datasets

We use five datasets for binary classification in Table 2 from the UCI Machine Learning Repository:\footnote{https://archive.ics.uci.edu/ml/index.php} We select diverse datasets with different domains, sizes, and dimensions.

Pre-trained models

We train MLPs for each dataset and use them as pre-trained source models in TRANS METER. Since we use the part of the features or training dataset in Sections 4.2 and 4.3, we also train MLPs using those datasets.

Baselines

We compare the results of TRANS METER with HeMap [Shi et al., 2010] and its variant. HeMap [Shi et al., 2010] is the most recent heterogeneous transfer learning method. HeMap samples source data near a given target data, and determines that it is too risky to transfer when the ratio of the selected source data is lower than a threshold. We exploit this ratio of the selected source data as a transferability between two datasets, and use this as a baseline method named HeMap. We also use the full-process of HeMap as a full-transfer algorithm.

As ablation studies, we further compare TRANS METER with its variants shown in Table 3.

4.2 Model Sanity Check

To verify that TRANS METER and its variants improve the accuracy of a target task, we perform self-transfer by transferring a source data to the feature-removed copy of the same data. For each dataset, we generate a new dataset by keeping only 20% of its features, and check whether TRANS METER and its variants improve the accuracy from transfer learning.

Table 4 shows the result of the self-transfer. Note that TRANS METER and its variants, except TRANS METER-0, improve the accuracy over the baseline on average and in most cases.

4.3 Ablation Study

We compare the performance of TRANS METER with those of its variants by measuring the transferability between all source and target pairs.

Table 5 shows the average transferability. Note that TRANS METER outperforms all of its variants, and shows positive transferabilities on average. We also observe that TRANS METER-A, TRANS METER-L, and TRANS METER-M outperform TRANS METER-0; it means the three improvements are meaningful. Based on the result, we select TRANS METER and TRANS METER-M as our best models when comparing to other competitors in Section 4.4.
Average Transferability

| Model         | Average Transferability |
|---------------|-------------------------|
| TRANS-METER   | 0.77                    |
| TRANS-METER-0 | -2.13                   |
| TRANS-METER-A | -0.91                   |
| TRANS-METER-L | -0.74                   |
| TRANS-METER-M | 0.59                    |

Table 5: Average transferability (%) of each model. TRANS-METER outperforms its variants.

### 4.4 Comparison to Competitors

We compare TRANS-METER to other methods for measuring transferability. We compare 1) the accuracies of the transferability measurement, and 2) the running times of all the methods. We use Spearman’s rank correlation coefficient between the predicted ranks and the ground truth ranks to evaluate the accuracy. Since TRANS-METER and TRANS-METER-M often improve the accuracy of the target task and outperform HeMap, we define the ground truth rank using the maximum accuracy of HeMap, TRANS-METER, and TRANS-METER-M for each source and target pair.

Figure 1 shows the results. Note that TRANS-METER and TRANS-METER-M provide the overall best accuracy. In terms of running time, HeMap is the slowest, but there is no clear winner among TRANS-METER, TRANS-METER-M, and HeMap. This shows that TRANS-METER and its variant give the most accurate transferability measurement, and their running times are not worse than competitors.

### 5 Conclusion

In this paper, we propose TRANS-METER, a novel algorithm that measures the transferability between two datasets. The base model of TRANS-METER comprises feature transformation layers, a label predictor, and domain classifiers. We use 1) a pre-trained source model as a label predictor to reduce the training time, and 2) domain classifier to reduce the gap between the source and the target domains. We improve the accuracy of the base model by introducing a reconstruction loss, label-wise discriminators, and a mean distance loss. Experiments show that TRANS-METER gives the best accuracy in measuring transferability, with comparable running time to those of competitors.

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