Practical Transferability Estimation for Image Classification Tasks

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Abstract

Transferability estimation is an essential problem in transfer learning to predict how good the performance is when transferring a source model (or source task) to a target task. Recent analytical transferability metrics have been widely used for source model selection and multi-task learning. A major challenge is how to make transferability estimation robust under the cross-domain cross-task settings. The recently proposed OTCE score solves this problem by considering both domain and task differences, with the help of transfer experiences on auxiliary tasks, which causes an efficiency overhead. In this work, we propose a practical transferability metric called JC-NCE score that dramatically improves the robustness of the task difference estimation in OTCE, thus removing the need for auxiliary tasks. Specifically, we build the joint correspondences between source and target data via solving an optimal transport problem with a ground cost considering both the sample distance and label distance, and then compute the transferability score as the negative conditional entropy of the matched labels. Extensive validations under the intra-dataset and inter-dataset transfer settings demonstrate that our JC-NCE score outperforms the auxiliary-task free version of OTCE for 7% and 12%, respectively, and is also more robust than other existing transferability metrics on average.

1 Introduction

Transferring a related pretrained source model to a new target task usually achieves higher performance than training from scratch on target data, especially when there are only few labeled target data for supervision [26, 28]. A common pitfall in selecting which source model to transfer is basing the selection on the source accuracy. In fact, higher source model accuracy does not always lead to higher transfer accuracy due to the non-trivial differences between source and target tasks, as shown in Figure 1. Therefore, understanding the relationship between source and target tasks is crucial to the success of transfer learning. Transferability characterizes such relationship via quantitatively evaluating how easy it is...
Figure 1: Transfer 40 source models (randomly generated 50-categories classification tasks, corresponding to each point in the figure) from Clipart, Painting, Quickdraw, Sketch domains to a target task (25-categories) in Real domain, which demonstrates that it is unreliable to perform source model selection according to the source model accuracy, but our JC-NCE score can predict the transfer performance more accurately.

to transfer the knowledge learned from a source task to the target task. In practical scenarios \([3, 21, 29, 30]\), we can apply a transferability metric to directly select the best source model for a target task rather than trying each source model on the target data, which involves expensive computation. In addition, transferability can help prioritize different tasks for joint training \([34]\) and multi-source feature fusion \([29]\).

Although theoretical analyses \([4, 6, 7, 18]\) in generalization bounds have suggested that the transfer performance could be attributed to several factors, e.g., certain divergence between source and target distributions, it is difficult to accurately estimate each factor from limited practical data. Meanwhile, previous empirical transferability metrics \([1, 33, 34]\) suffer heavy computation burdens in retraining the source model to obtain the training loss or validation accuracy for indicating transferability. Recent analytical transferability metrics \([9, 11, 22, 31]\) are evidently more efficient to compute from practical data, but there also exists some drawbacks, e.g., strict data assumptions \([1, 11]\), insufficient performance \([22]\). And the state-of-the-art method OTCE \([29]\) requires auxiliary tasks with known transfer accuracy for calculating the coefficients of a linear model, which involves extra computations and restricts its application scenarios.

Consequently, Tan et al. \([29]\) also propose a simplified version of OTCE, namely OT-based NCE score, that does not depend on auxiliary tasks. It builds a soft correspondence between source and target data via solving an Optimal Transport (OT) problem, and then use the Negative Conditional Entropy (NCE) between the coupled source and target labels to characterize transferability. However, their correspondences only depend on the marginal distribution of input samples, without considering the label information. While it still outperforms previous auxiliary-task free metrics including NCE \([31]\), H-score \([1]\) and LEEP \([21]\), it is more reasonable to utilize both the sample information and the label information to build the joint correspondences between source and target datasets.

Motivated by this idea, we propose the JC-NCE (Joint Correspondences Negative Conditional Entropy) score to further improve the transferability estimation performance. Inspired by recent OTDD \([1]\) method, we define the ground cost metric in the OT problem as a weighted combination of the sample distance and the label distance. By solving the OT problem, we can obtain the joint probability distribution of source and target data and then compute our JC-NCE score as the negative conditional entropy. We conduct extensive cross-domain cross-task transfer experiments to validate the superior performance of our JC-NCE score. Specifically, we first follow the same intra-dataset experimental settings as the OT-based NCE score, i.e., perform transfer learning on two cross-domain datasets DomainNet \([25]\) and Office31 \([7]\). Results show that our JC-NCE score outperforms the OT-based
NCE score with 7% gain on average. Moreover, we conduct the inter-dataset evaluation. We select 15 source models and 7 target datasets from the VTAB [36] benchmark to perform cross-dataset transfer. Results also show that our method outperforms the OT-based NCE score with about 12% gain. In addition, we analyze the effect of hyper parameter and compare the computation efficiency among existing metrics.

In summary, our main contribution is proposing a practical transferability metric JC-NCE score which is easier to use and more efficient than the state-of-the-art OTCE score and more accurate than the simplified version OT-based NCE score with up to 12% gain.

2 Related Works

Theoretical analyses [4, 5, 6, 7, 18, 19] of generalization bounds have summarized several factors affecting the transfer performance, which also inspires the study in transferability estimation. For instance, Ben-David et al. [5, 6] attribute the transfer performance to the empirical risk of source task, the distance between source and target data, and the discrepancy of labeling functions. However, it is difficult to verify whether the assumptions of these theoretical works are satisfied on practical data and even more difficult to compute exactly.

Several empirical transferability estimation methods [1, 32, 34] are proposed to deal with practical tasks. Taskonomy [34] propose a transferability score named task affinity which is computed by retraining the source model on target tasks and then evaluating the transfer performance. Task2Vec [1] retrains a large scale probe neural network on target tasks and then compute the Fisher information matrix to produce embedding vectors. Measuring the distance between vectors will indicate the transferability. Ying et al. [32] propose to learn previous transfer skills for future target tasks. Generally, empirical methods usually require heavy computation in retraining neural network, which is not superior to directly using the empirical risk of the retrained source model on target tasks.

Recent analytical transferability metrics [3, 21, 29, 30] mostly avoid the expensive computation for retraining the source model and can efficiently estimate the transferability, which is useful in source model selection. However, they still have limitations. NCE [30] assumes both the source and target tasks are defined on the same data instances. H-score [3] assumes the same data distribution of the source and target tasks. LEEP [21] does not work sufficiently well under the challenging cross-domain cross-task transfer settings. Although OTCE [29] achieves the state-of-the-art performance, it requires several auxiliary tasks with known transfer accuracy for determining the linear combination of the domain difference and the task difference, which brings extra computation and is not achievable in some scenarios. Alternatively, Tan et al. [29] also propose a simplified version of the OTCE score, namely OT-based NCE score, which still can be further improved.

3 Method

In this section, we first present the definition of transferability for classification tasks, and then introduce the main concepts of previous OT-based NCE score [29]. Then we propose our JC-NCE score.
3.1 Transferability Definition

Formally, we have source data \( D_s = \{(x_i^s, y_i^s)\}_{i=1}^{m} \sim P_s(x, y) \) and target data \( D_t = \{(x_i^t, y_i^t)\}_{i=1}^{n} \sim P_t(x, y) \), where \( x_i^s, x_i^t \in \mathcal{X} \) and \( y_i^s, y_i^t \in \mathcal{Y} \). Meanwhile, \( P(x_s) \neq P(x_t) \) and \( \mathcal{Y}_s \neq \mathcal{Y}_t \) indicate different domains and tasks respectively. In addition, we are given a source model \((\theta_s, h_s)\) pretrained on source data \( D_s \), in which \( \theta_s : \mathcal{X} \rightarrow \mathbb{R}^d \) represents a feature extractor producing \( d \)-dimensional features and \( h_s : \mathbb{R}^d \rightarrow \mathcal{P}(\mathcal{Y}_s) \) is the head classifier predicting the final probability distribution of labels, where \( \mathcal{P}(\mathcal{Y}_s) \) is the space of all probability distributions over \( \mathcal{Y}_s \).

For neural network based transfer learning, there are two representative paradigms [10, 11], i.e., Retrain head [10] and Finetune [11]. The Retrain head method keeps the weights of source feature extractor \( \theta_s \) frozen and retracts a new head classifier \( h_t \). But the Finetune method updates the source feature extractor and the head classifier simultaneously to obtain new \((\theta_t, h_t)\). Compared to Retrain head, Finetune trade-offs transfer efficiency for better transfer accuracy and it requires more target data to avoid overfitting [12]. Usually, we choose Retrain head when there are only few labeled target data.

To obtain the empirical transferability, we need to retrain the source model via Retrain head or Finetune on target data and then evaluate the expected log-likelihood on its testing set. Formally, the empirical transferability is defined as:

**Definition 1** The empirical transferability from source task \( S \) to target task \( T \) is measured by the expected log-likelihood of the retrained \((\theta_s, h_t)\) or \((\theta_t, h_t)\) on the testing set of target task:

\[
\text{Trf}(S \rightarrow T) = \begin{cases} 
\mathbb{E} \left[ \log P(y_t|x_t; \theta_s, h_t) \right] & \text{(Retrain head)} \\
\mathbb{E} \left[ \log P(y_t|x_t; \theta_t, h_t) \right] & \text{(Finetune)}
\end{cases}
\]

which indicates how good the transfer performance is on target task \( T \). [29, 30]

Although the empirical transferability can be the golden standard of describing how easy it is to transfer the knowledge learned from a source task to a target task, it is computationally expensive to obtain. Analytical transferability metric is a function of the source and target data that efficiently approximates the empirical transferability, i.e., the ground-truth of the transfer performance on target tasks.

3.2 Preliminary of OT-based NCE Score [29]

Before detailing our proposed JC-NCE score, we briefly introduce the main concepts of previous OT-based NCE score to facilitate the context. Tan et al. [29] propose a unified framework named OTCE, which characterize the domain difference and the task difference between source and target tasks, and use the linear combination of domain difference and task difference to describe transferability. Specifically, the OTCE score first estimates the joint probability distribution \( \hat{P}(x_s, x_t) \) of source and target input instances via solving an Optimal Transport (OT) problem [13], which also produces the Wasserstein distance (domain difference). Then based on \( \hat{P}(x_s, x_t) \), we can obtain \( \hat{P}(y_s, y_t) \) and \( \hat{P}(y_s) \) for calculating the Conditional Entropy \( H(Y_t|Y_s) \) (task difference).

However, although the OTCE score shows high correlation with the transfer accuracy, it requires several auxiliary tasks (at least 3) with known transfer accuracy to learn the coefficients of the linear combination under a specified transfer configuration, which involves expensive computation in obtaining the transfer accuracy of auxiliary tasks. Moreover, the
learned coefficients cannot generalize to other configurations due to the variations of data and source models. To omit the learning process, they also propose an alternative efficient implementation named **OT-based NCE** score which only uses the *task difference* to characterize transferability. In other words, the OT-based NCE score trade-offs accuracy for a simpler and more efficient transferability estimation.

### 3.3 JC-NCE Score

Here we propose the JC-NCE score which not only preserves the simplicity and efficiency as the OT-based NCE score but also shows higher transferability estimation performance. We also follow the framework proposed by the OT-based NCE score, i.e., build the correspondences between source and target data, and then compute the negative conditional entropy $-H(Y_t|Y_s)$ for describing transferability.

We adopt the ground cost metric proposed by recent OTDD [3] method for building the joint correspondences, which is a weighted combination of the sample distance and the label distance. Specifically, the computation process of our JC-NCE score is described as follows.

First, we define the sample instances of source and target tasks as $z_s = (x_s, y_s)$ and $z_t = (x_t, y_t)$ respectively, where $z_s \in Z_s = \mathcal{X} \times \mathcal{Y}_s$ and $z_t \in Z_t = \mathcal{X} \times \mathcal{Y}_t$. And we define the $\alpha_s \triangleq P(X|Y = y)$, which can be estimated from a collection of finite samples with label $y$. Then the cost function can be defined as:

$$d(z_s, z_t) \triangleq \lambda c(\theta_s(x_s), \theta_t(x_t)) + (1 - \lambda)W(\alpha_{y_s}, \alpha_{y_t}), \quad (2)$$

where $c(\cdot, \cdot) = \| \cdot - \cdot \|_2^2$ is the cost metric of sample distance. And $W(\alpha_{y_s}, \alpha_{y_t})$ is the 1-Wasserstein distance between labels, where the cost metric is also $c(\cdot, \cdot)$. $\lambda \in [0, 1]$ is a hyper parameter to combine the sample distance and the label distance, and here we let $\lambda = 0.5$. More discussion about $\lambda$ is described in Section 4.3. It has been shown in [3] that Equation (2) is a proper metric and a good choice for the ground cost in defining the optimal transport problem between two joint distributions $P(z_s)$ and $P(z_t)$.

Consequently, the OT problem is defined as:

$$OT(D_s, D_t) \triangleq \min_{\pi \in \Pi(D_s, D_t)} \sum_{i,j=1}^{m,n} d(z_s^i, z_t^j) \pi_{ij}, \quad (3)$$

where $\pi$ is the coupling matrix of size $m \times n$, representing the correspondences between source and target data. After solving this OT problem\(^1\), we obtain the optimal coupling.

\(^1\)The OT problem can be efficiently solved by the POT library: https://pythonot.github.io
matrix \( \pi^* \). Then the empirical joint probability distribution of source and target labels, and the marginal probability distribution of source label can be easily computed as below:

\[
\hat{P}(y_s, y_t) = \sum_{i,j} \pi^*_{ij}, \quad \hat{P}(y_s) = \sum_{y_t \in Y_t} \hat{P}(y_s, y_t).
\]

(4)

Then we can compute the JC-NCE score as the negative conditional entropy,

\[
\text{JC-NCE} = -H(Y_t | Y_s) = \sum_{y_t \in Y_t} \sum_{y_s \in Y_s} \hat{P}(y_s, y_t) \log \frac{\hat{P}(y_s, y_t)}{\hat{P}(y_s)}.
\]

(5)

Previous work NCE \([30]\) has shown that the empirical transferability is lower bounded by the negative conditional entropy,

\[
\tilde{\text{Trf}}(S \rightarrow T) \geq l_S(\theta_s, h_s) - H(Y_t | Y_s),
\]

(6)

where the training log-likelihood \( \tilde{\text{Trf}}(S \rightarrow T) = l_T(\theta_s, h_t) = \frac{1}{n} \sum_{i=1}^{n} \log P(y_t^i | x_t^i; \theta_s, h_t) \) is an approximation of the empirical transferability when the retrained model is not overfitted. And \( l_S(\theta_s, h_s) \) is a constant, so the empirical transferability can be attributed to the conditional entropy.

We show a toy example in Figure 2 to compare the optimal coupling results of the OT-based NCE score and our JC-NCE score. It can be seen that our JC-NCE score produces a more reasonable coupling between source and target data, i.e., ensure a better label-to-label matching result which leads to a more robust estimation targeting to the classification accuracy.

4 Experiments

We conduct extensive cross-domain cross-task transfer learning experiments to evaluate the effectiveness of our proposed JC-NCE score. First, we investigate the performance under the intra-dataset transfer setting, i.e., source task and target task are generated from the same dataset but different sub-domains. We adopt the largest-to-date cross-domain dataset DomainNet \([25]\) and the popular Office31 \([27]\) dataset. Furthermore, we study the inter-dataset transfer setting, i.e., source task and target task are defined on different datasets. We follow the configurations of VTAB \([36]\), a large-scale visual task adaptation benchmark. Finally, we make some analysis on the hyper parameter \( \lambda \) and the computation efficiency.

4.1 Evaluation on Intra-Dataset Transfer Setting

Tasks in this setting are generated by sampling different sets of categories from two popular cross-domain datasets including:

- **DomainNet** \([25]\) contains images distributing in six domains (styles) including **Clipart (C)**, **Infograph (I)**, **Painting (P)**, **Quickdraw (Q)**, **Real (R)** and **Sketch (S)**. Each domain covers 345 common object categories. Following the experimental configuration of \([25]\), we exclude **Infograph** for its noisy annotations and restrict the number of instances per category to be at most 100.
Office31 is a representative benchmark dataset in transfer learning area. It contains 4,110 images distributing in three domains, i.e., Amazon (A), DSLR (D) and Webcam (W). Each domain covers 31 categories typically found in office environment.

For fair comparison, we follow the same experimental set-ups in OT-based NCE, i.e., the standard configuration in which tasks have different category size, and the more challenging fixed category size configuration. We also use Pearson correlation coefficient like to evaluate the correlation between the transfer accuracy and the transferability score. We train eight ResNet-18 neural networks (5 for DomainNet, 3 for Office31) as source models for each domain targeting to the randomly generated source tasks. Specifically, the source task for DomainNet is a randomly sampled 44-category classification task, and the source task for Office31 is a 15-category classification task.

For standard evaluation, we conduct 2,000 (5 × 4 × 100) cross-domain cross-task transfer tests on DomainNet, and 600 (3 × 2 × 100) tests on Office31. Specifically, we successively take one domain as the source domain, and rests are target domains. For each target domain, we randomly sample 100 classification tasks where the number of categories range from 10 to 100 for DomainNet, and 10 to 31 for Office31. The transfer accuracy on target task is the testing accuracy after retraining the head classifier of source model on target data with SGD optimizer and cross-entropy loss for 100 epochs.

The Fixed category size evaluation is a more challenging configuration since it requires the transferability score to capture the more subtle variations of domain and the task relatedness except for the intrinsic complexity of the target task. Thus in this configuration, we randomly sample 100 target tasks with 50 categories for each target domain to keep similar task complexities, and other settings are the same as the standard evaluation.

Table 1 shows the comparisons among our JC-NCE score and other analytical transferability metrics, including the OT-based NCE, LEEP, NCE and H-score in both experimental configurations. The average correlation scores of JC-NCE are 0.914 and 0.615 respectively, which significantly outperforms the compared methods. In particular, under the fixed category size configuration, the JC-NCE score achieves a 13% improvement compared to the state-of-the-art OT-based NCE score. This improvement can be visually captured in Figure 3, where the transferability scores of target tasks in domain Quickdraw (in red) can be better estimated via the JC-NCE score. More visual comparisons are shown in the Supplementary.

Figure 3: Visualization of the correlations between the transfer accuracy and transferability scores under the challenging fixed category size setting, where all target tasks (50-categories classification, corresponding to each point in the figure) have similar complexities. Our JC-NCE score significantly outperforms the OT-based NCE score, especially as illustrated in the green circle.
### Table 1: Quantitative comparisons evaluated by Pearson correlation coefficients between the transfer accuracy and transferability scores under the intra-dataset transfer setting.

| Config | Source domain | Target domain | JC-NCE | OT-based NCE | LEEP | NCE | H-score |
|--------|---------------|---------------|--------|--------------|------|-----|---------|
| Standard | C, P, Q, R, S | 0.952 | 0.960 | 0.919 | 0.787 | -0.864 |
|          | P, C, Q, R, S | 0.953 | 0.952 | 0.886 | 0.812 | -0.858 |
|          | Q, C, P, R, S | 0.968 | 0.963 | 0.942 | 0.935 | -0.843 |
|          | R, C, P, Q, S | 0.957 | 0.951 | 0.892 | 0.851 | -0.870 |
|          | S, C, P, Q, R | 0.951 | 0.959 | 0.952 | 0.954 | -0.882 |
|          | A, D, W | 0.817 | 0.813 | 0.805 | 0.796 | -0.590 |
|          | D, A, W | 0.867 | 0.843 | 0.857 | 0.849 | -0.441 |
|          | W, A, D | 0.845 | 0.803 | 0.811 | 0.804 | -0.489 |
| Average | 0.914 | 0.906 | 0.883 | 0.849 | -0.730 |

| Fixed category size | C, P, Q, R, S | 0.754 | 0.729 | 0.614 | 0.535 | 0.599 |
|                     | P, C, Q, R, S | 0.711 | 0.647 | 0.480 | 0.418 | 0.541 |
|                     | Q, C, P, R, S | 0.427 | 0.306 | 0.213 | 0.269 | 0.288 |
|                     | R, C, P, Q, S | 0.677 | 0.587 | 0.465 | 0.440 | 0.100* |
|                     | S, C, P, Q, R | 0.506 | 0.443 | 0.381 | 0.427 | 0.302 |
| Average | 0.615 | 0.542 | 0.431 | 0.418 | 0.366 |

Superscript * denotes $p > 0.001$, and bold denotes the best result, and underline denotes the 2nd best result.

### Table 2: Quantitative comparisons evaluated by Pearson correlation coefficients between the transfer accuracy and transferability scores under the inter-dataset transfer setting. The upper part represents transferring via Finetune, and the lower part represents Retrain head.

| Method | Caltech101 | CIFAR-100 | DTD | Flowers102 | Pets | Camelyon | SVHN | Avg |
|--------|------------|-----------|-----|------------|------|-----------|------|-----|
| JC-NCE | 0.784 | 0.938 | 0.905 | 0.973 | 0.915 | 0.646* | 0.670* | 0.833 |
| OT-based NCE | 0.685* | 0.764 | 0.819 | 0.779 | 0.818 | 0.494* | 0.592* | 0.707 |
| H-score | 0.680* | 0.957 | 0.970 | 0.991 | 0.980 | 0.693* | 0.666* | 0.848 |
| JC-NCE | 0.935 | 0.939 | 0.903 | 0.919 | 0.963 | 0.710* | 0.887 | 0.894 |
| OT-based NCE | 0.891 | 0.906 | 0.869 | 0.856 | 0.981 | 0.735* | 0.686* | 0.846 |
| H-score | 0.983 | 0.879 | 0.952 | 0.973 | 0.877 | 0.898 | 0.932 | 0.928 |

Superscript * denotes $p > 0.001$, and bold denotes the best result, and underline denotes the 2nd best result.

### 4.2 Evaluation on Inter-Dataset Transfer Setting

We further study the performance under the inter-dataset transfer setting, where source models are provided by the Visual Task Adaptation Benchmark (VTAB) [36]. The model zoo contains 15 models trained on ImageNet by different algorithms, e.g., supervised learning (Sup-100%), semi-supervised learning (Semi-rotation-10% and Semi-exemplar-10% [35]), self-supervised learning (Rotation [11] and Jigsaw [23]), generative method (Cond-biggan [8]) and VAEs [15], etc. For target tasks, we introduce 7 image classification datasets including Caltech101 [17], CIFAR-100 [16], DTD [9], Flowers102 [22], Pets [24], SVHN [20] and Camelyon [31]. More information about source models and target datasets is described in the Supplementary.

Specifically, we transfer source models to each target task via two transfer methods, i.e., Retrain head (only retrain a new head classifier) and Finetune (finetune all weights). We follow the transfer accuracy reported in VTAB. As the VTAB model zoo only publicly provides feature extractors, we are unable to make comparisons with the LEEP and NCE scores since they require the entire source model for predicting the pseudo labels on target...
data so that they cannot be used for transferring feature extractor only.

We show the correlation comparisons among our JC-NCE, OT-based NCE and H-score in Table 2. Our JC-NCE score also outperforms the OT-based NCE score. Note that H-score achieves slightly better correlation results than JC-NCE. Because the source dataset and most target datasets come from the natural environment so that the domain gap is small, which satisfies the data assumption of H-score. However, in the previous intra-dataset experiment (Table 1), H-score is negatively correlated with the transfer performance, failing to estimate the cross-domain transferability score. Therefore, we conclude that JC-NCE is a more robust and practical metric overall. Visual comparisons are included in the Supplementary.

We also make comparisons in source model selection shown in Table 3. Each target task has 15 candidate source models and we want to verify whether the source model with the highest transferability score is the best source model (with highest transfer accuracy). We calculate the Top-k (k=1,2,3) selecting accuracy and found that the JC-NCE, OT-based NCE and H-score achieved comparable good results, i.e., the ground-truth best model can be selected from the predicted Top-3 highest transferable models in most cases.

Table 3: The Top-k accuracy of the best source model selection under the inter-dataset transfer setting, i.e., select the best one from 15 source models for 7 target tasks according to their transferability scores. The upper and lower parts represent transferring via Finetune and Retrain head respectively.

| Method          | Top-1 | Top-2 | Top-3 |
|-----------------|-------|-------|-------|
| JC-NCE          | 1 / 7 | 5 / 7 | 5 / 7 |
| OT-based NCE    | 2 / 7 | 7 / 7 | 7 / 7 |
| H-score         | 2 / 7 | 5 / 7 | 5 / 7 |
| JC-NCE          | 3 / 7 | 5 / 7 | 6 / 7 |
| OT-based NCE    | 3 / 7 | 4 / 7 | 5 / 7 |
| H-score         | 2 / 7 | 4 / 7 | 6 / 7 |

Table 4: Computation time statistics.

| Method                  | Time     |
|-------------------------|----------|
| Empirical transferability| 858s (14.3min) |
| LEEP                    | 0.06s    |
| NCE                     | 0.007s   |
| H-score                 | 0.11s    |
| OT-based NCE            | 0.41s    |
| JC-NCE                  | 1.87s    |

### Figure 4: Analysis of $\lambda$

#### 4.3 Effect of Parameter $\lambda$

We study the effect of the hyper parameter $\lambda \in [0, 1]$ in Equation (2), which determines the impacts of the sample distance and the label distance in computing the joint correspondences of source and target datasets. As shown in Figure 4, the JC-NCE score achieves the highest performance when let $\lambda = 0.5$. 
4.4 Efficiency Analysis

We compare the computation time among transferability metrics shown in Table 4. Specifically, the empirical transferability is computed on GPU (NVIDIA GTX1080Ti) through retraining the source model (ResNet-18) on target data and then evaluating the log-likelihood on the testing set. For analytical metrics, we randomly sample 1,000 instances for computation (on CPU). Results demonstrate that analytical transferability metrics are evidently more efficient and easier to obtain than the empirical transferability. More implementation details are introduced in the Supplementary.

5 Conclusion

In this paper, we propose JC-NCE score, a practical transferability metric for classification tasks. It preserves the simplicity and efficiency of the previous OT-based NCE method, but significantly improves its transferability estimation performance by considering both the sample distance and the label distance simultaneously. Extensive experiments in both the intra-dataset and the inter-dataset settings demonstrate that our JC-NCE score works more robustly than previous analytical transferability metrics. In future works, we will investigate how to use JC-NCE to benefit downstream applications in heterogeneous transfer learning and multi-task learning.

References

[1] Alessandro Achille, Michael Lam, Rahul Tewari, Avinash Ravichandran, Subhransu Maji, Charless C Fowlkes, Stefano Soatto, and Pietro Perona. Task2vec: Task embedding for meta-learning. pages 6430–6439, 2019.

[2] David Alvarez-Melis and Nicolo Fusi. Geometric dataset distances via optimal transport. In Advances in Neural Information Processing Systems, volume 33, pages 21428–21439, 2020.

[3] Yajie Bao, Yang Li, Shao-Lun Huang, Lin Zhang, Lizhong Zheng, Amir Zamir, and Leonidas Guibas. An information-theoretic approach to transferability in task transfer learning. In 2019 IEEE International Conference on Image Processing (ICIP), pages 2309–2313. IEEE, 2019.

[4] Shai Ben-David and Reba Schuller. Exploiting task relatedness for multiple task learning. In Learning Theory and Kernel Machines, pages 567–580. Springer, 2003.

[5] Shai Ben-David, John Blitzer, Koby Crammer, and Fernando Pereira. Analysis of representations for domain adaptation. Advances in neural information processing systems, 19:137–144, 2006.

[6] Shai Ben-David, John Blitzer, Koby Crammer, Alex Kulesza, Fernando Pereira, and Jennifer Wortman Vaughan. A theory of learning from different domains. Machine learning, 79(1-2):151–175, 2010.

[7] John Blitzer, Koby Crammer, Alex Kulesza, Fernando Pereira, and Jennifer Wortman. Learning bounds for domain adaptation. In Advances in neural information processing systems, pages 129–136, 2008.
Andrew Brock, Jeff Donahue, and Karen Simonyan. Large scale gan training for high fidelity natural image synthesis. *International Conference on Learning Representations*, 2019.

M. Cimpoi, S. Maji, I. Kokkinos, S. Mohamed, , and A. Vedaldi. Describing textures in the wild. In *IEEE Conference on Computer Vision and Pattern Recognition*, 2014.

Jeff Donahue, Yangqing Jia, Oriol Vinyals, Judy Hoffman, Ning Zhang, Eric Tzeng, and Trevor Darrell. Decaf: A deep convolutional activation feature for generic visual recognition. In *International conference on machine learning*, pages 647–655, 2014.

Spyros Gidaris, Praveer Singh, and Nikos Komodakis. Unsupervised representation learning by predicting image rotations. In *International Conference on Learning Representations*, 2018.

Ross Girshick, Jeff Donahue, Trevor Darrell, and Jitendra Malik. Rich feature hierarchies for accurate object detection and semantic segmentation. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 580–587, 2014.

Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 770–778, 2016.

LV Kantorovich. On the translocation of masses, cr (dokl.) acad. *Sci. URSS (NS)*, 37: 199, 1942.

Diederik P Kingma and Max Welling. Auto-encoding variational bayes. *arXiv preprint arXiv:1312.6114*, 2013.

Alex Krizhevsky. Learning multiple layers of features from tiny images. Technical report, 2009.

Fei-Fei Li, Rob Fergus, and Pietro Perona. One-shot learning of object categories. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2006.

Yishay Mansour, Mehryar Mohri, and Afshin Rostamizadeh. Domain adaptation: Learning bounds and algorithms. *arXiv preprint arXiv:0902.3430*, 2009.

Andreas Maurer. Transfer bounds for linear feature learning. *Machine learning*, 75(3): 327–350, 2009.

Yuval Netzer, Tao Wang, Adam Coates, Alessandro Bissacco, Bo Wu, and Andrew Y. Ng. Reading digits in natural images with unsupervised feature learning. In *NIPS Workshop on Deep Learning and Unsupervised Feature Learning 2011*, 2011.

Cuong V Nguyen, Tal Hassner, Cedric Archambeau, and Matthias Seeger. Leep: A new measure to evaluate transferability of learned representations. In *International Conference on Machine Learning*, 2020.

M-E. Nilsback and A. Zisserman. Automated flower classification over a large number of classes. In *Indian Conference on Computer Vision, Graphics and Image Processing*, Dec 2008.
[23] Mehdi Noroozi and Paolo Favaro. Unsupervised learning of visual representations by solving jigsaw puzzles. In *European Conference on Computer Vision*, 2016.

[24] O. M. Parkhi, A. Vedaldi, A. Zisserman, and C. V. Jawahar. Cats and dogs. In *IEEE Conference on Computer Vision and Pattern Recognition*, 2012.

[25] Xingchao Peng, Qin Xin Bai, Xide Xia, Zijun Huang, Kate Saenko, and Bo Wang. Moment matching for multi-source domain adaptation. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 1406–1415, 2019.

[26] Lorien Y Pratt. Discriminability-based transfer between neural networks. In *Advances in neural information processing systems*, pages 204–211, 1993.

[27] Kate Saenko, Brian Kulis, Mario Fritz, and Trevor Darrell. Adapting visual category models to new domains. In *European conference on computer vision*, pages 213–226. Springer, 2010.

[28] Qianru Sun, Yaoyao Liu, Tat-Seng Chua, and Bernt Schiele. Meta-transfer learning for few-shot learning. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 403–412, 2019.

[29] Yang Tan, Yang Li, and Shao-Lun Huang. Otce: A transferability metric for cross-domain cross-task representations. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 15779–15788, June 2021.

[30] Anh T Tran, Cuong V Nguyen, and Tal Hassner. Transferability and hardness of supervised classification tasks. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 1395–1405, 2019.

[31] Bastiaan S Veeling, Jasper Linmans, Jim Winkens, Taco Cohen, and Max Welling. Rotation equivariant cnns for digital pathology. In *International Conference on Medical Image Computing and Computer-Assisted Intervention*, 2018.

[32] Wei Ying, Yu Zhang, Junzhou Huang, and Qiang Yang. Transfer learning via learning to transfer. In *International Conference on Machine Learning*, pages 5085–5094, 2018.

[33] Jason Yosinski, Jeff Clune, Yoshua Bengio, and Hod Lipson. How transferable are features in deep neural networks? In *Advances in neural information processing systems*, pages 3320–3328, 2014.

[34] Amir R Zamir, Alexander Sax, William Shen, Leonidas J Guibas, Jitendra Malik, and Silvio Savarese. Taskonomy: Disentangling task transfer learning. pages 3712–3722, 2018.

[35] Xiaohua Zhai, Avital Oliver, Alexander Kolesnikov, and Lucas Beyer. S4l: Self-supervised semi-supervised learning. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 1476–1485, 2019.

[36] Xiaohua Zhai, Joan Puigcerver, Alexander Kolesnikov, Pierre Ruysse, Carlos Riquelme, Mario Lucic, Josip Djolonga, Andre Susano Pinto, Maxim Neumann, Alexey Dosovitskiy, et al. A large-scale study of representation learning with the visual task adaptation benchmark. *arXiv preprint arXiv:1910.04867*, 2019.

[37] Wen Zhang, Lingfei Deng, and Dongrui Wu. Overcoming negative transfer: A survey. *arXiv preprint arXiv:2009.00909*, 2020.