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L5 – Transfer learning and domain adaptation

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Transfer Learning

A Comprehensive Survey on Transfer Learning

This survey provides a comprehensive understanding of transfer learning from the perspectives of data and model.

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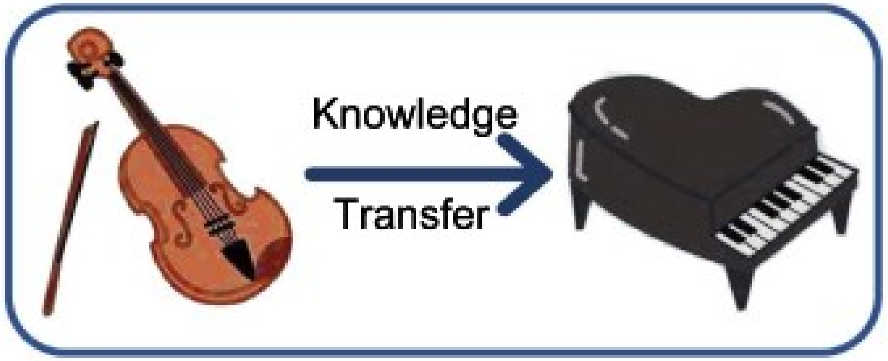
ABSTRACT | Transfer learning aims at improving the performance of target learners on target domains by transferring the knowledge contained in different but related source domains. In this way, the dependence on a large number of target-domain data can be reduced for constructing target learners. Due to the wide application prospects, transfer learning has become a popular and promising area in machine learning. Although there are already some valuable and impressive surveys on transfer learning, these surveys introduce approaches in a relatively isolated way and lack the recent advances in transfer learning. Due to the rapid expansion of the transfer learning area, it is both necessary and challenging to comprehensively review the relevant studies. This survey attempts to connect and systematize the existing transfer learning research studies, as well as to summarize and interpret the mechanisms and the strategies of transfer learning in a comprehensive way, which may help readers have a better understanding of the current research status and ideas. Unlike previous surveys, this survey article reviews more than 40 representative transfer learning approaches, especially homogeneous transfer learning approaches, from the perspectives of data and model. The applications of transfer learning are also briefly introduced. In order to show the performance of different transfer learning models, over 20 representative transfer learning models are used for experiments. The models are performed on three different data sets, that is, Amazon Reviews, Reuters-21578, and Office-31, and the experimental results demonstrate the importance of selecting appropriate transfer learning models for different applications in practice.

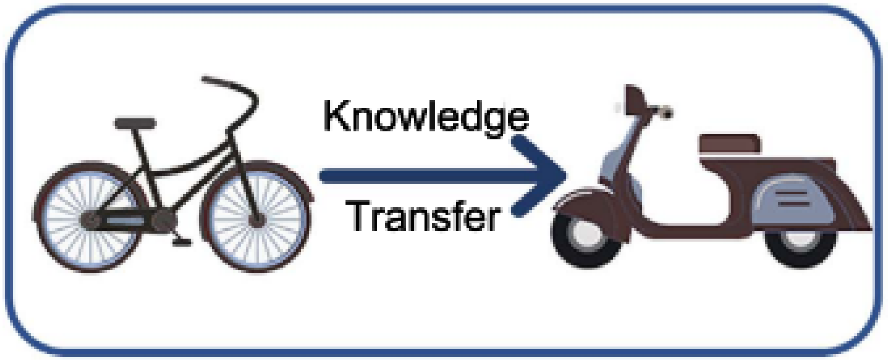
KEYWORDS | Domain adaptation; interpretation; machine learning; transfer learning.

NOMENCLATURE

Symbol	Definition
n	Number of instances.
m	Number of domains.
$\mathcal{D}$	Domain.
$\mathcal{T}$	Task.
$\mathcal{X}$	Feature space.
$\mathcal{Y}$	Label space.
$\mathbf{x}$	Feature vector.
y	Label.
X	Instance set.
Y	Label set corresponding to X.

In a nutshell: knowledge transfer





Taxonomy

Instance-based Inductive Deep Transfer Learning by Cross-Dataset Querying with Locality Sensitive Hashing

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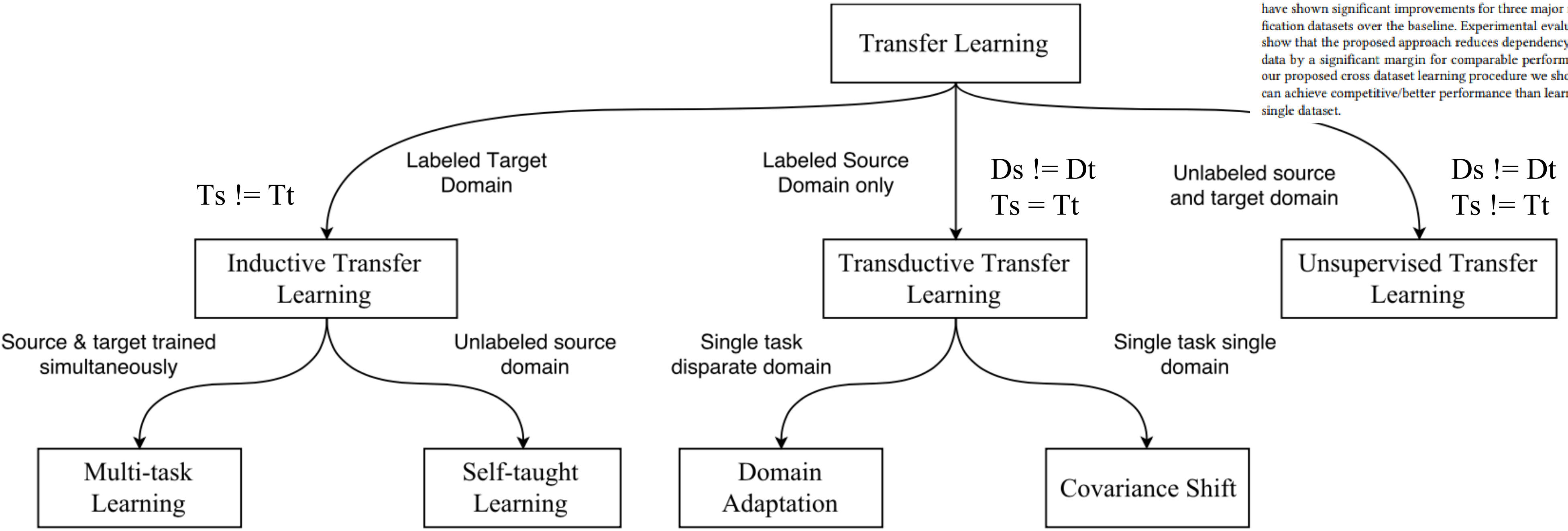
ABSTRACT

Supervised learning models are typically trained on a single dataset and the performance of these models rely heavily on the size of the dataset, i.e., amount of data available with the ground truth. Learning algorithms try to generalize solely based on the data that is presented with during the training. In this work, we propose an inductive transfer learning method that can augment learning models by infusing similar instances from different learning tasks in the Natural Language Processing (NLP) domain. We propose to use instance representations from a source dataset, *without inheriting anything* from the source learning model. Representations of the instances of *source & target* datasets are learned, retrieval of relevant source instances is performed using soft-attention mechanism and *locality sensitive hashing*, and then, augmented into the model during training on the target dataset. Our approach simultaneously exploits the local *instance level information* as well as the macro statistical viewpoint of the dataset. Using this approach we have shown significant improvements for three major news classification datasets over the baseline. Experimental evaluations also show that the proposed approach reduces dependency on labeled data by a significant margin for comparable performance. With our proposed cross dataset learning procedure we show that one can achieve competitive/better performance than learning from a single dataset.

weights in order to fit a subset of the original learning task. Transfer learning suffers heavily from domain inconsistency between tasks and may even have a negative effect [29] on performance. Domain adaptation techniques aim to predict unlabeled data given a pool of labeled data from a similar domain. In domain adaptation, the aim is to have better generalization as source and target instances are assumed to be coming from different probability distributions, even when the underlying task is same.

We present our approach in an *inductive transfer learning* [26] framework, with a labeled *source* (domain $\mathcal{D}_S$ and task $\mathcal{T}_S$) and *target* (domain $\mathcal{D}_T$ and task $\mathcal{T}_T$) dataset, the aim is to boost the performance of target predictive function $f_T(\cdot)$ using available knowledge in $\mathcal{D}_S$ and $\mathcal{T}_S$, given $\mathcal{T}_S \neq \mathcal{T}_T$. We retrieve instances from $\mathcal{D}_S$ based on similarity criteria with instances from $\mathcal{D}_T$, and use these instances while training to learn the target predictive function $f_T(\cdot)$. We utilize the instance-level information in the source dataset, and also make the newly learnt target instance representation similar to the retrieved source instances. This allows the learning algorithm to improve generalization across the source and target datasets. We use *instance-based learning* that actively looks for similar instances in the source dataset given a target instance. The intuition behind retrieving similar instances comes from an instance-based learning perspective, where simplification of the class distribution takes place within the locality of a test instance. As a result, modeling



Neural networks enable transferability

The inherent weighting scheme of neural network-based models allows transferability

This means that we can either:

- modify weights to generate a new model
- freeze weights and add another set of weights that are learned on the task and/or domain. The combination of the 2 generate a new model

Transfer learning in operation

Certain portions of the learned model are re-trained for fine-tuning, meaning that we alter the weights of the network

The aim is to customize the model for the domain and/or task of analysis

Domain adaptation in operation

The model remains the same

The aim is to predict unlabelled data given a pool of labelled data from a **similar** domain

Application of foundation models

Foundation models are generated from massive data. This feature generates an output that is general enough to be utilized in a multitude of domains

This is a peculiar strenght of these models and it largely applied in a domain adaption setting

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Thank you for your attention.

Questions?

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