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Applied Data Science Project

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 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.

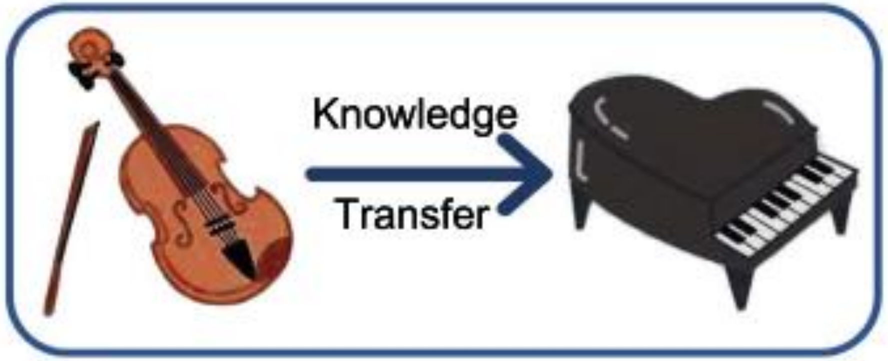
KEYWORDS | Domain adaptation; interpretation; machine learning; transfer learning.

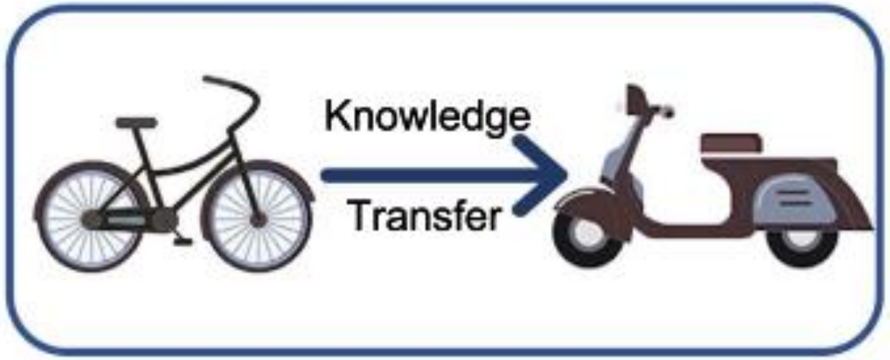
NOMENCLATURE

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.

https://arxiv.org/abs/1911.02685

In a nutshell: knowledge transfer





Definitions

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.

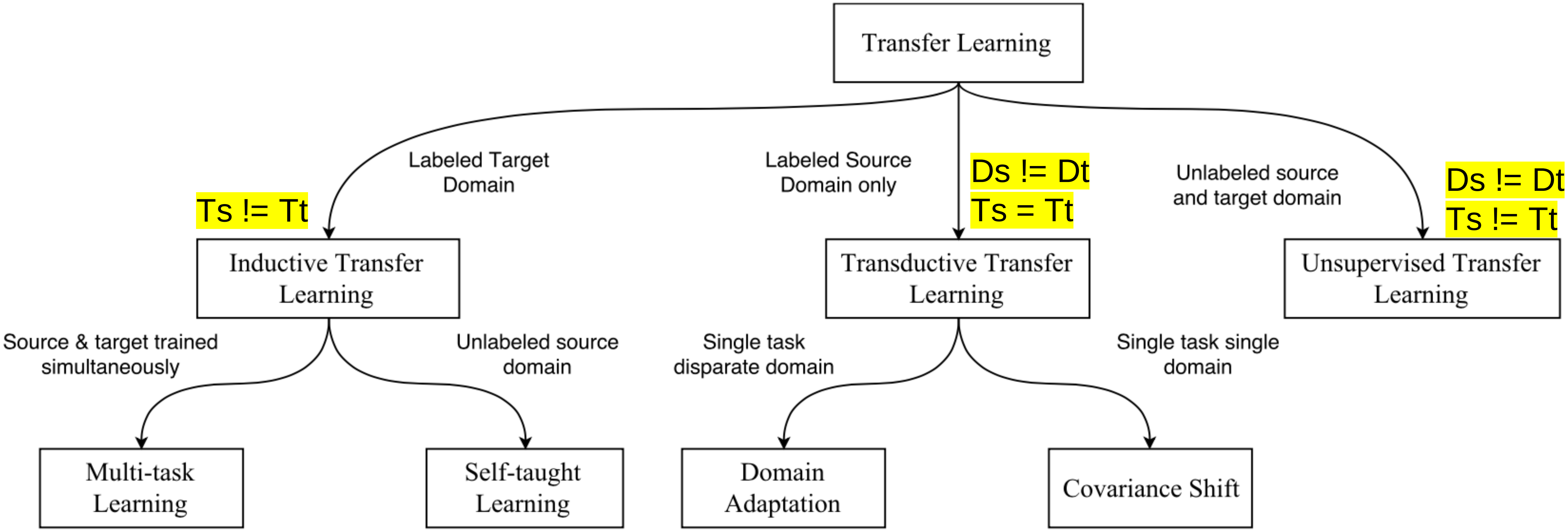
We present our approach in an *inductive transfer learning* [26] framework, with a labeled *source* (domain $\mathcal{D}_S$ and task $\mathcal{T}_S$) and *target* (domain $\mathcal{D}_T$ and task $\mathcal{T}_T$) dataset, the aim is to boost the performance of target predictive function $f_T(\cdot)$ 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

https://arxiv.org/abs/1802.05934

Let's define:

T = Task
D= Domain
s= source
t=target

Taxonomy


Transfer Learning
Labeled Target Domain
Labeled Source Domain only
Unlabeled source and target domain
Ts != Tt
Ds != Dt
Ts = Tt
Ds != Dt
Ts != Tt
Inductive Transfer Learning
Transductive Transfer Learning
Unsupervised Transfer Learning
Source & target trained simultaneously
Unlabeled source domain
Single task disparate domain
Single task single domain
Multi-task Learning
Self-taught Learning
Domain Adaptation
Covariance Shift

Transfer learning

Goal: applying knowledge learned from one task (often a related or even a completely different task) to another task

Domains: The source and target domains can be different, but the knowledge learned from the source can still be useful in the target. For example, knowledge from object detection in images could be applied to facial recognition

Tasks: The tasks in the source and target domains are different, but the features or representations learned from the source domain are reused in the target task

Transfer learning: image classification

Classifying animals

Classifying cancer

Transfer learning: natural language processing

WebText

Introduced by Radford et al. in Language Models are Unsupervised Multitask Learners

WebText is an internal OpenAI corpus created by scraping web pages with emphasis on document quality. The authors scraped all outbound links from Reddit which received at least 3 karma. The authors used the approach as a heuristic indicator for whether other users found the link interesting, educational, or just funny.

WebText contains the text subset of these 45 million links. It consists of over 8 million documents for a total of 40 GB of text. All Wikipedia documents were removed from WebText since it is a common data source for other datasets.

Writing text mimicking the content of articles

Question:

What is the capital of France?

Answer:

The capital of France is **Paris**.

Answering to questions

Domain adaptation

Goal: Focusing on adapting a model trained in a source domain to perform well in a different but related target domain

Domains: The source and target domains are different, but the task remains the same. The key challenge here is adapting the model to work well in the new domain, which has a different data distribution than the source domain

Tasks: The task remains the same, but the data distribution is different

Domain adaptation: object detection

Recognizing a dog

Recognizing a dog

Domain adaptation: sentiment analysis

Movie: *Inception (2010)*

Rating: ★★★★★ (5/5)

Review: *"Inception" is a mind-bending masterpiece by Christopher Nolan that challenges the boundaries of storytelling and visual effects. The intricate plot, which weaves through multiple layers of dreams, keeps viewers on the edge of their seats from start to finish. Leonardo DiCaprio delivers a compelling performance as Cobb, a man driven by guilt and loss, while the ensemble cast supports the film's complex narrative beautifully. The special effects, particularly in the dream sequences, are breathtaking, making "Inception" a truly immersive experience. This movie is not just a visual spectacle but also a thought-provoking exploration of reality and perception.*

Classyfing sentiment

Product: *XYZ Front Load Washing Machine - 7kg*

Rating: ★★★★☆ (4/5)

Review Title: *Great performance but a bit noisy*

Review: I've been using this washing machine for about 3 months now, and overall, I'm quite satisfied with its performance. It handles large loads effortlessly, and the spin cycle leaves clothes nearly dry, which saves time in the dryer. The different wash settings are great, especially the quick wash option for lightly soiled clothes.

However, I did notice that it's a bit noisier than I expected during the spin cycle. It's not unbearable, but if your laundry room is near living areas, it might be noticeable. Other than that, the machine is efficient, energy-saving, and has a sleek design. For the price, it's a solid purchase.

Classyfing sentiment

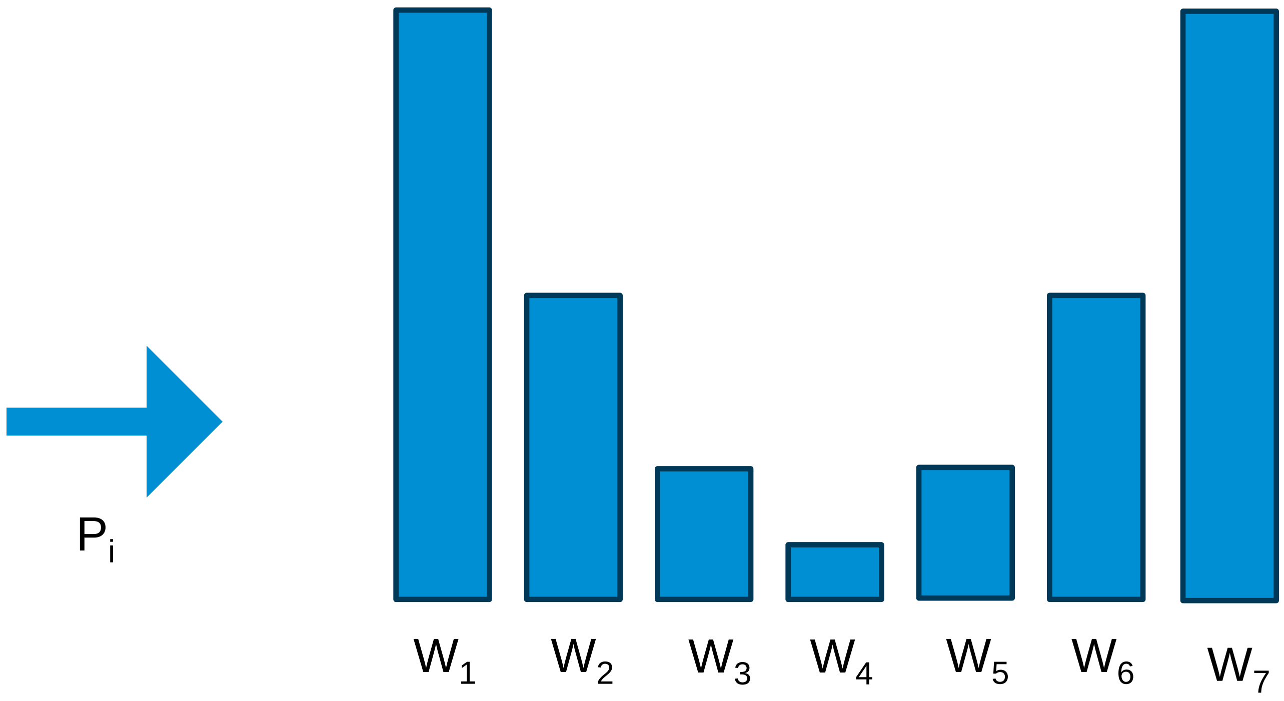
Neural networks enable transferability

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
- optimizing parameters

Which weights and parameters?



P_i = learning rate, batch size, regularization techniques

W_i = weights and biases of the neural layers

Updating potentially all W_i and potentially all P_i

However, the update of all has a cost that is proportional with the dimension of the network

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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