A Comprehensive Survey on Transfer Learning

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# Introduction

According to psychologist C.H. Judd, learning to transfer is the result of the generalization of experience.

* Qr code

  Description automatically generatedPrerequisite is that there needs to be a connection between two learning activities.

## Negative Transfer

* Transfer learning (TL) doesn’t always bring positive impact on new tasks
  + Learning to ride bicycle cannot help us learn piano faster
* Negative Transfer depend on relevance between source and target domains and the learner’s capacity to find the transferable and beneficial parts of the knowledge across the domains
  + Learning Spanish can make it difficult to learn French though the languages share a lot in common, as previous learning interferes with learning word formation, usage, pronunciation, etc. in French.

## Homogeneous Transfer

* This paper focused on Homogeneous Transfer Learning
* Domains are in the same feature space
* Differ only in marginal distributions - dealt by correcting sample selection bias or covariate shift.
* This assumption doesn’t hold in some cases, i.e. word may have different meaning in different domains i.e. context feature bias – Adapt conditional distributions

## Heterogeneous Transfer

* Knowledge transfer where domains have different feature space
* Requires feature space adaptation in addition to distribution adaptation
* More complicated
* Not a focus for this paper
* Also not covered are Reinforcement Transfer Learning, Lifelong Transfer Learning & Online Transfer Learning

## Aim of the Survey

* Over 40 Representative Transfer Learning approached are summarized
* Experiments are conducted to compare over 20 different approaches

# Related Areas

Areas related to TL are:

## Semi-Supervised Learning (SSL)

* Combines abundant un-labeled with a limited number of labeled instances to train a learner
* Relaxes the dependence on labeled instances thereby reducing labeling costs
* Both instances are drawn from same distribution
* In contrasts, the distributions of source and target domains are different in Transfer Learning
* Key assumptions of smoothness, cluster, and manifold hold both in case of semi-supervised and transfer learning
* Many a times TL absorbs the technology of SSL

## Multi-View Learning (MVL)

* MVL focuses on ML for multi-view data – Object is described from multiple views
* Example: Video Object with image signal and audio signal
* Learning can be improved by considering information from all the available views
* Strategies include – Subspace Learning, Multi-kernel learning, and co-training
* Approaches are also adopted in TL – Zhang et al. proposed a multi-view TL framework which imposes the consistency among multiple views
* Yang and Gao – Multi-view information across different domains for knowledge transfer
* Feuz and Cook – Multi-view TL for activity learning: Knowledge transfer between heterogenous sensor platform

## Multi-Task Learning (MTL)

* Jointly learn a group of related tasks
* Reinforces each task by taking advantage of interconnections
* Considers inter-task relevance and inter-task difference – enhances generalization
* MTL vs TL: MTL pays equal attention to each task; TL pays more attention to Target task
* Zhang et al. employs MTL and TL for biological image analysis
* Liu et al. proposes a framework for human-action recognition based on MTL and TL

# Overview

## Definitions

* Domain (***D***): comprises of feature space ***X*** and a marginal distribution ***P(X)***
* Task (***T***): consists of label space ***Y*** and a decision function ***f*** to be learned from the data
* Transfer Learning (**TL**): Utilized knowledge implied in source domain to improve performance of the learned decision function ***fT*** on the target domain
* Domain Adaptation: Process of adapting one or more source domains to transfer knowledge and improve the performance of the target learner

## Categorization of Transfer Learning

Diagram

Description automatically generated

### Problem Categories

#### Based on Label Information

* + Transductive TL – Only source domain has label information
  + Inductive TL – Both source and target domain have label information
  + Unsupervised TL – Neither source nor target domain have label information

#### Based on Feature Space and Label Space

* + Homogeneous TL – Both Feature Space and Label space of source and target domains are similar
  + Heterogenous TL – Either Feature Space or Label Space or both not similar for source and target domains

### Solution Categories

#### Instance Based

* + Instance weighting strategy

#### Feature Based

* + Transforms the original features to create new feature representation
  + Symmetric Transformation – Attempts to find common feature latent space and then transform both the source and the target
  + Asymmetric Transformation – Transforms source features to match target ones

#### Parameter Based

* + Transfer of knowledge at model/parameter level

#### Relational Based

* + Focus on problems in relational domain
  + Transfer of logical relationship or rules learned
  + This survey does not cover Relational-based approaches

# Data-based Interpretation

Broadly covers instance based and feature based transfer learning. Focused on transferring the knowledge via the adjustment and the transformation of the data.

Diagram

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## Strategies

* Instance Weighting
* Feature Transformation

## Objectives

* Space Adaptation – Mostly required in Heterogenous TL – Not a focus for this paper
* Distribution Adaptation – Main objective in case of Homogeneous TL: To reduce the distribution difference between the source and the target domain instances
* Data Property Preservation/Adjustment – Certain advanced approaches and use cases

## Instance Weighting Strategy

* Large number of labeled source domain and a limited number of target domain instances are available
* Domains differ in only marginal distributions i.e. P(Xs) ≠ P(Xt) but P(Y|Xs) = P(Y|Xt)
* Adapting the marginal distributions by assigning weights to the source-domain instances in the loss function

## Feature Transformation Strategy

### Distribution Difference Metric

### Feature Augmentation

### Feature Mapping

### Featuring Clustering

### Feature Selection

### Feature Encoding

### Feature Alignment

# Model-based Interpretation

Broadly covers parameter based approaches.

## Model Control Strategy

## Parameter Control Strategy

### Parameter Sharing

### Parameter Restriction

## Model Ensemble Strategy

#### Candidate Classifier Construction

#### Classifier Selection and Ensemble

#### Graph Construction

#### Learner Weighting

#### Anchor Selection

#### Anchor-based Representation Generation

#### Learner Training and Ensemble

## Deep Learning Technique

### Traditional Deep Learning

### Adversarial Deep Learning

# Application

## Medical Application

## Bioinformatics Application

## Transportation Application

## Recommender-System Application

## Other Applications

### Communication Application

### Urban-Computing Application

# Experiment

## Dataset and Preprocessing

### Amazon Reviews

### Reuters-21578

### Office-31

## Experiment Setting

## Experiment Result

# Conclusion & Future Direction