Transfer Learning summary

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Transfer Learning

- **Introduction**
- Definition of TL
- Categorization of TL
  - Instance-based
    - Noninductive
    - Inductive
  - Feature-based
  - Model-based
  - Relation-based
- Heterogeneous TL
- Negative Transfer
- TL with Deep Learning
- Fundamental Research Issues
- Applications of TL
- References

Introduction

- Transfer Learning deals with how learning systems can quickly adapt themselves to new situations, new tasks and new environments[TLB].

- Transfer learning aims at improving the performance of target learners on target domains by transferring the knowledge contained in different but related source domains[ARX].

Introduction

- *Machine learning*: Machines can acquire knowledge through labeled and unlabeled data.

- *Data as "teachers":* Machine learning algorithms produces prediction models from data.

- *Labeled training data:* Observations and outcomes of predictions are coupled and correlated.

Introduction

What causes the problem:

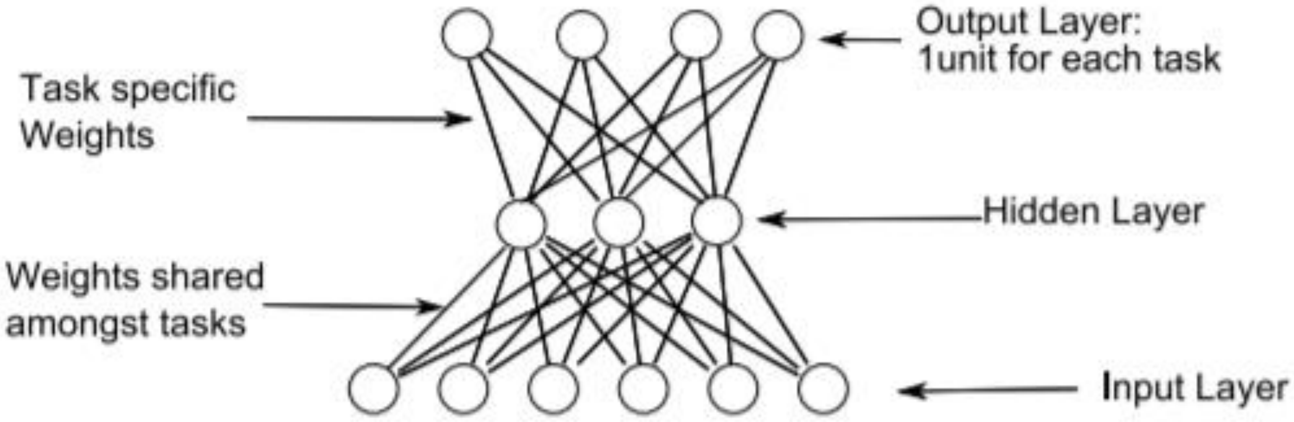
- Lack of new labeled training data or small amount of data.
- The data distribution between domains varies (changes of circumstances).
- Changes of tasks.

Introduction

Why we weed transfer learning:

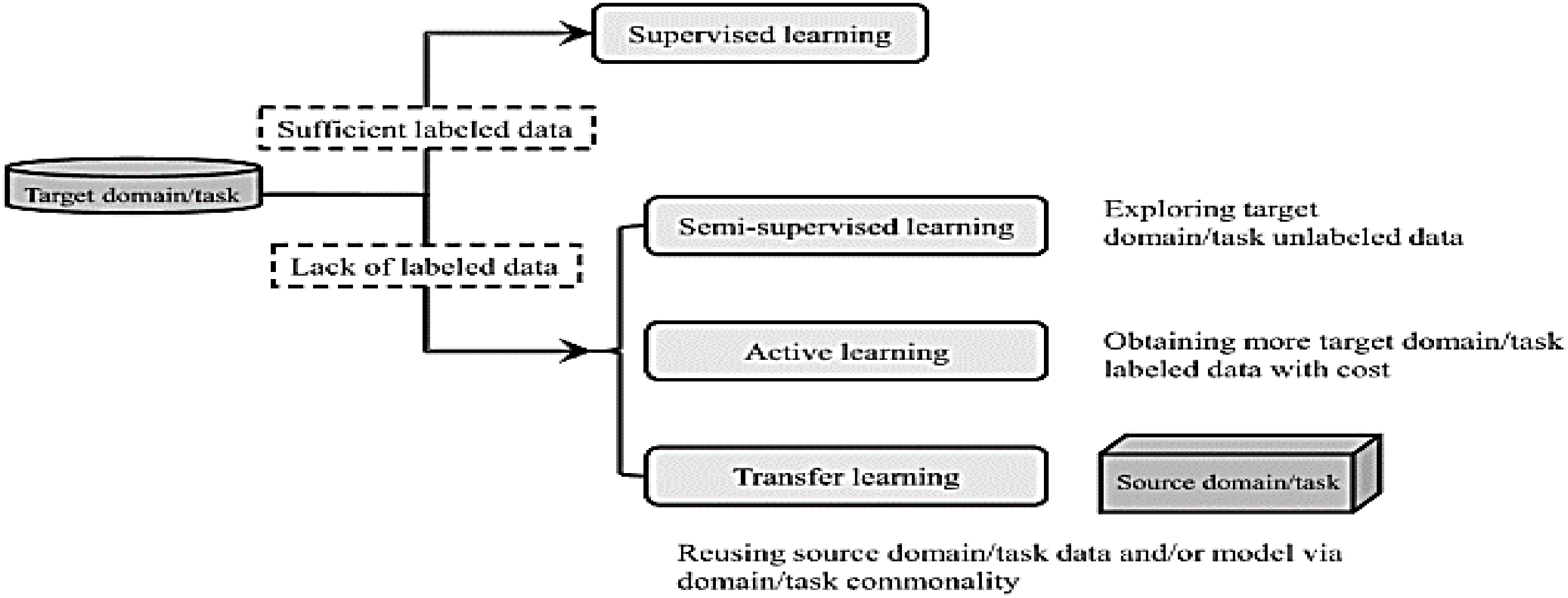
- Traditional machine learning methods often cannot generalize well to new scenarios or tasks (overfitting).
- Training and test data are not drawn from the same distribution and the trained models need adaptation before using.
- The problem of cold start, when we try to adapt a general model to a specific situation.

Introduction



A typical Transfer Learning Method (from [NIPS])

Introduction



Relationship of transfer learning to other learning paradigms (from [TLB])

Transfer Learning

- Introduction
- **Definition of TL**
- Categorization of TL
  - Instance-based
    - Noninductive
    - Inductive
  - Feature-based
  - Model-based
  - Relation-based
- Heterogeneous TL
- Negative Transfer
- TL with Deep Learning
- Fundamental Research Issues
- Applications of TL
- References

Definition of TL

Basic notations:

- **Domain** [JD92, TLB]:

$$D = (X, P(X))$$

  - X: feature space
  - $P(X)$: marginal distribution where $X = \{X_1, X_2, \dots, X_n\}$

- **Task** [JD92, TLB]:

$$T = (Y, f(\cdot))$$

  - Y: label space
  - $f(\cdot)$:objective predictive function.

Definition of TL

- **Sourse Domain** $D_s = \{(x_{s_i}, y_{s_i})_{i=1}^{n_s}\}$ with labeled data where $x_{s_i} \in X_s$ is the data instance and $y_{s_i} \in Y_s$ is the corresponding class label.

- **Target Domain** $D_t = \{(x_{t_i}, y_{t_i})_{i=1}^{n_t}\}$ with labeled data where $x_{t_i} \in X_t$ is the data instance and $y_{t_i} \in Y_t$ is the corresponding class label.

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Definition of TL

- **Transfer Learning:** Given a source domain D_s and learning task T_s, a target domain D_t and learning task T_t, aims to help improve the learning of the target predictive function $f_t(\cdot)$ for the target domain using the knowledge in D_s and T_s, where $D_s \neq D_t \; or \; T_s \neq T_t$.

- When $D_s \neq D_t$ either $X_s \neq X_t$ or $\mathrm{P}(X_s) \neq P(X_t)$.

  When $T_s \neq T_t$ either $Y_s \neq Y_t$ or $\mathrm{P}(Y_s|X_s) \neq P(Y_t|X_t)$.
  - When $D_s = D_t$ and $T_s = T_t$ the learning problem becomes a traditional machine learning problem.

Transfer Learning

- Introduction
- Definition of TL
- **Categorization of TL**
    - Instance-based
        - Noninductive
        - Inductive
    - Feature-based
    - Model-based
    - Relation-based
- Heterogeneous TL
- Negative Transfer
- TL with Deep Learning
- Fundamental Research Issues
- Applications of TL
- References

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Categorization of TL

- Transfer learning problems (label-setting aspect):

1. *Transductive*: label information only comes from the source domain.

2. *Inductive*: label information of the target-domain instances is available.

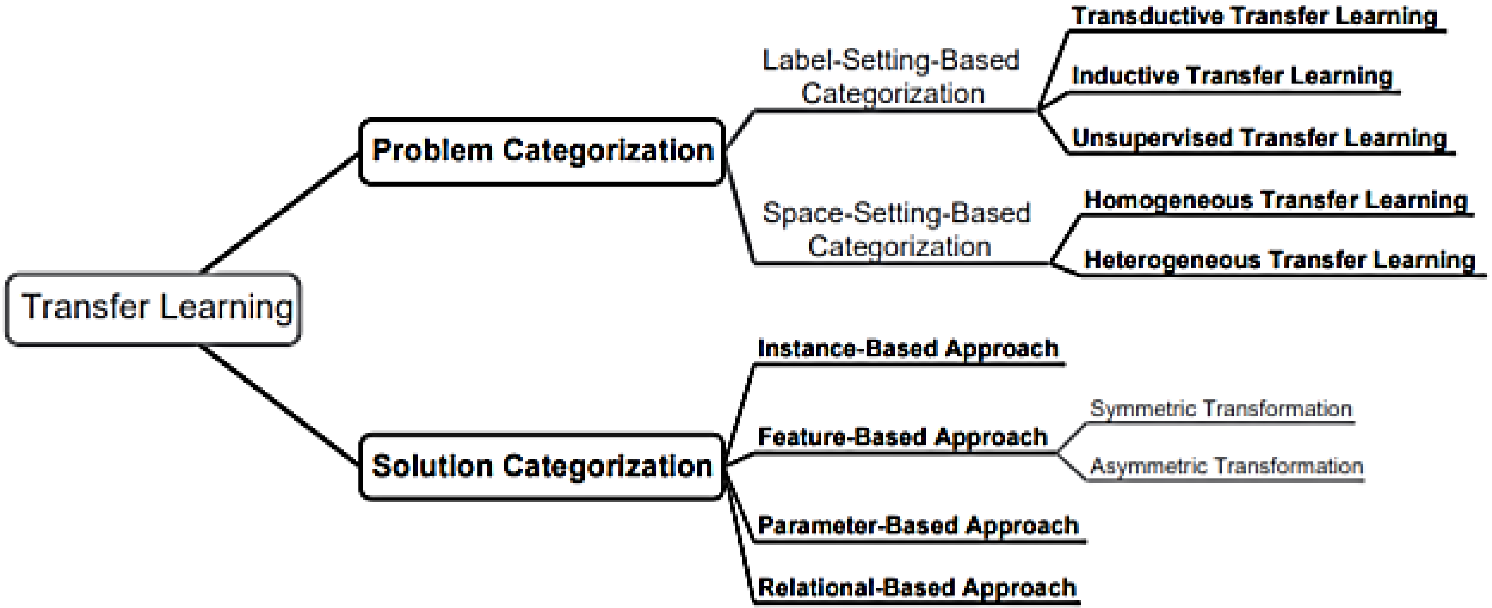
3. *Unsupervised*: label information is unknown for both the source and the target domains.

Categorization of TL

- Consistency between the source and the target feature spaces and label spaces:

1. Homogeneous transfer learning $X_S = X_T$ and $Y_S = Y_T$.
2. Heterogeneous transfer learning $X_S \neq X_T$ and $Y_S \neq Y_T$.

Categorization of TL



Categorization of Transfer Learning (from [ARX])

Transfer Learning

- Introduction
- Definition of TL
- Categorization of TL
  - **Instance-based**
    - Noninductive
    - Inductive
  - Feature-based
  - Model-based
  - Relation-based
- Heterogeneous TL
- Negative Transfer
- TL with Deep Learning
- Fundamental Research Issues
- Applications of TL
- References

Instance-based TL

- Reuse source's domain labeled data to train a model for a learning task in a target domain, minimizing the vagueness.
- Small target's domain data set leads to high variance and model's generalization error is large. We can reduce variance by using appropriate source's domain labeled data as an auxiliary data set in the target's domain learning task.
- Different data distributions in the two domains causes the new learning model to have a high bias.

Instance-based TL

- Main issues to resolve:
  - How to distinguish which source domain-labeled instances are similar to the target domain ones.
  - How to use these "similar” source domain-labeled instances to train an algorithm in the target domain.
- Common assumptions:
  - The input instances of the source domain and the target domain have similar range of values.
  - The output labels of the source and target tasks are the same.

Transfer Learning

- Introduction
- Definition of TL
- Categorization of TL
    - Instance-based
        - **Noninductive**
        - Inductive
    - Feature-based
    - Model-based
    - Relation-based
- Heterogeneous TL
- Negative Transfer
- TL with Deep Learning
- Fundamental Research Issues
- Applications of TL

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Instance-based Noninductive TL

- We assume that the source task and the target task are the same and

$$X_s \approx X_T$$

$$P_S(X) \neq P_T(X) \ \ \textbf{but} \ \ P_S(Y|X) = P_T(Y|X)$$

- We are able to train a precise model for a target learning task even without having a set of target domain labeled data.

Transfer Learning

- Introduction
- Definition of TL
- Categorization of TL
  - Instance-based
    - Noninductive
    - **Inductive**
  - Feature-based
  - Model-based
  - Relation-based
- Heterogeneous TL
- Negative Transfer
- TL with Deep Learning
- Fundamental Research Issues
- Applications of TL
- References

Instance-based Inductive TL

- Conditional probabilities in source task and target task, are different.

$$P_s\ (Y|X) \neq P_T\ (Y|X)$$

- We need at least a small set of target domain-labeled data as inputs

$$D_T = \{(x_{T_i}, y_{T_i})\}_{i=1}^{n_T}$$

- The goal is to learn a precise predictive model for the target domain unseen data, by adapting $P_s\ (Y|X)$ in order to accurate establish $P_t\ (Y|X)$.

Transfer Learning

- Introduction
- Definition of TL
- Categorization of TL
  - Instance-based
    - Noninductive
    - Inductive
  - **Feature-based**
  - Model-based
  - Relation-based
- Heterogeneous TL
- Negative Transfer
- TL with Deep Learning
- Fundamental Research Issues
- Applications of TL
- References

Feature-based TL

- [TLB, JD92, ARX] An idea behind feature-based approaches is to learn a “good” feature representation for both the source domain and the target domain such that, by projecting data onto the new representation, the source domain labeled data can be reused to train a precise classifier for the target domain.

Feature-based TL

- *Minimizing divergence across domains*: A set of latent features (factors) or components are responsible for observing high-dimensional data instances and a subset of them can cause the difference between domains.
- We must identify those latent factors (features) that do not cause the domain discrepancy and use them to come with a representation of the data instances across domains.

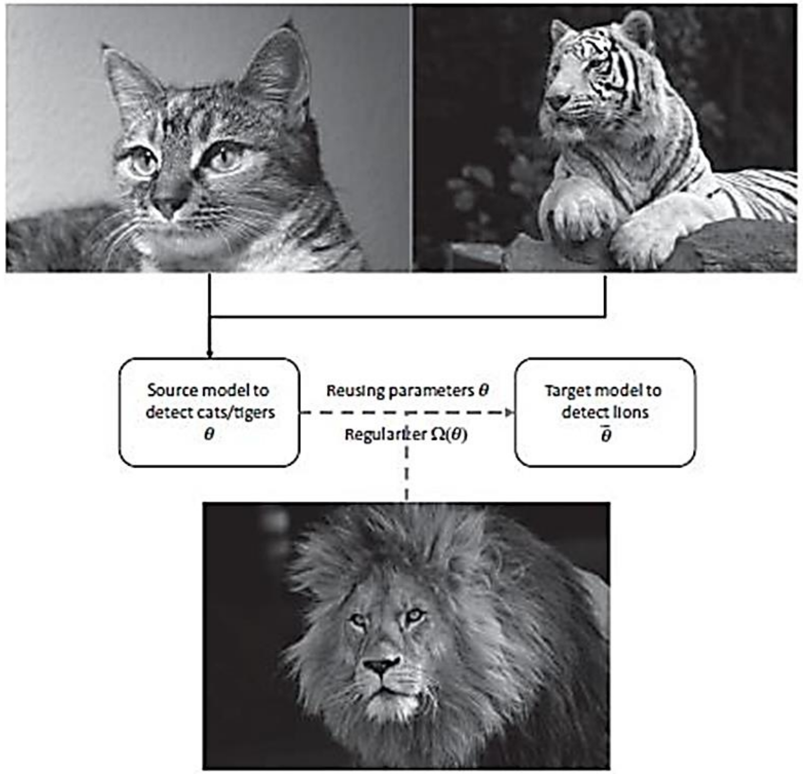
Transfer Learning

- Introduction
- Definition of TL
- Categorization of TL
  - Instance-based
    - Noninductive
    - Inductive
  - Feature-based
  - **Model-based**
  - Relation-based
- Heterogeneous TL
- Negative Transfer
- TL with Deep Learning
- Fundamental Research Issues
- Applications of TL
- References

Model-based TL

- Makes the assumption that there is a common knowledge, in the model level, between the source and the target task that is encoded into model parameters or model architectures.
- Model-based TL aims to discover what part of the model learned in the source domain we can use to help learning for the target domain.
- In Model-based transfer learning we don’t need to resample the training data or conduct relational inference on complicate data representations.

Model-based TL



Adapt the parameter θ to detect a new class “lions” $\tilde{\theta}$ using a regularizer $\Omega(\cdot)$ (from [TLB])

Transfer Learning

- Introduction
- Definition of TL
- Categorization of TL
  - Instance-based
    - Noninductive
    - Inductive
  - Feature-based
  - Model-based
  - **Relation-based**
- Heterogeneous TL
- Negative Transfer
- TL with Deep Learning
- Fundamental Research Issues
- Applications of TL
- References

Relation-based TL

- Relation-based TL aims to build the mapping of the relational knowledge between the source relational domain and the target relational domain, based on the assumption that the relations among the data in the source domain and the target domain have common regularities.

- Two mechanisms of relation-based TL:
  - First-order relation-based TL.
  - Second-order relation-based TL.

Relation-based TL

- Transfer knowledge through regularization:

  Some domains in the real world contain structures among data instances. These structures can lead to relational structures in domains. Classical machine learning methods implicitly assume that data instances are indented, but in a relational domain this assumption is not valid.

- Poor performance of learning models on relational domains:
  - Insufficient data.
  - Changes in the relational domain.
  - When there are many kinds of relations between data instances.

Transfer Learning

- Introduction
- Definition of TL
- Categorization of TL
  - Instance-based
    - Noninductive
    - Inductive
  - Feature-based
  - Model-based
  - Relation-based
- **Heterogeneous TL**
- Negative Transfer
- TL with Deep Learning
- Fundamental Research Issues
- Applications of TL
- References

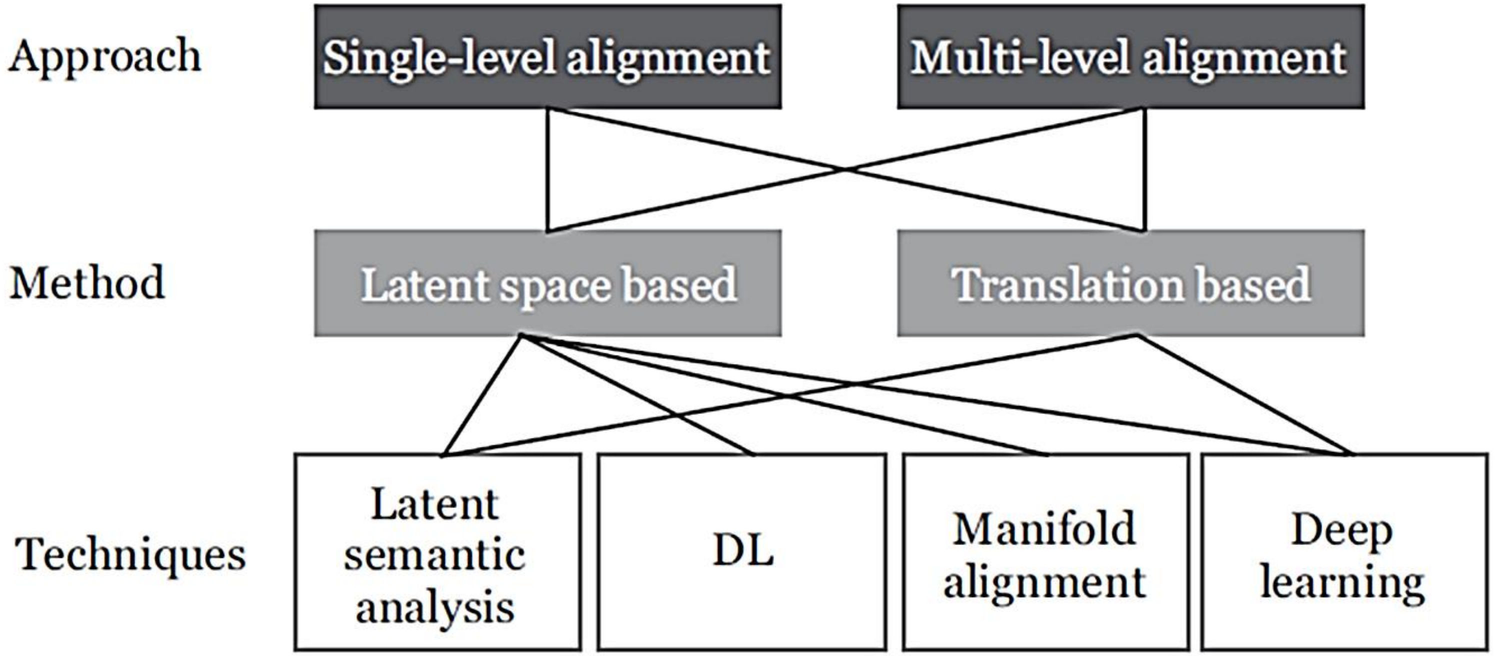
Heterogeneous TL

- Heterogeneous TL Problem:

  Feature Spaces of source and target domains are different $X_s \neq X_t$ or label spaces of the two domains are different $Y_s \neq Y_t$. Given a source domain D_s and a target domain D_t:

  - Learn what knowledge to transfer from the D_s to improve $P_T\ (Y|X)$ in D_T (reducing generalization error on unseen data)
  - Having as few as possible labeled data n_t^l for training in D_T and with $P_T\ (Y|X)$ to perform the same degree of generalization.

Heterogeneous TL



The hierarchical categorization of methodologies for heterogeneous TL (from [TLB])

Heterogeneous TL

Approach \ Techniques	Latent space based				Translation based
	Latent factor analysis	DL	Manifold alignment	Deep learning	
Single-level alignment	✓	✓	✓		✓
Multi-level alignment		✓		✓	✓

Research works so far (from [TLB])

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Transfer Learning

- Introduction
- Definition of TL
- Categorization of TL
  - Instance-based
    - Noninductive
    - Inductive
  - Feature-based
  - Model-based
  - Relation-based
- Heterogeneous TL
- **Negative Transfer**
- TL with Deep Learning
- Fundamental Research Issues
- Applications of TL
- References

Negative Transfer

- **Negative** transfer happens when source domain data and task contribute to **reduced** performance of learning in the target domain. [JD92, NT, JO]

- **Negative Transfer Conditions:**
  - Domains are too dissimilar[NT]
  - Conditional Kolmogorov complexity is not related[JD92]
  - Tasks are not well-related[JD92]

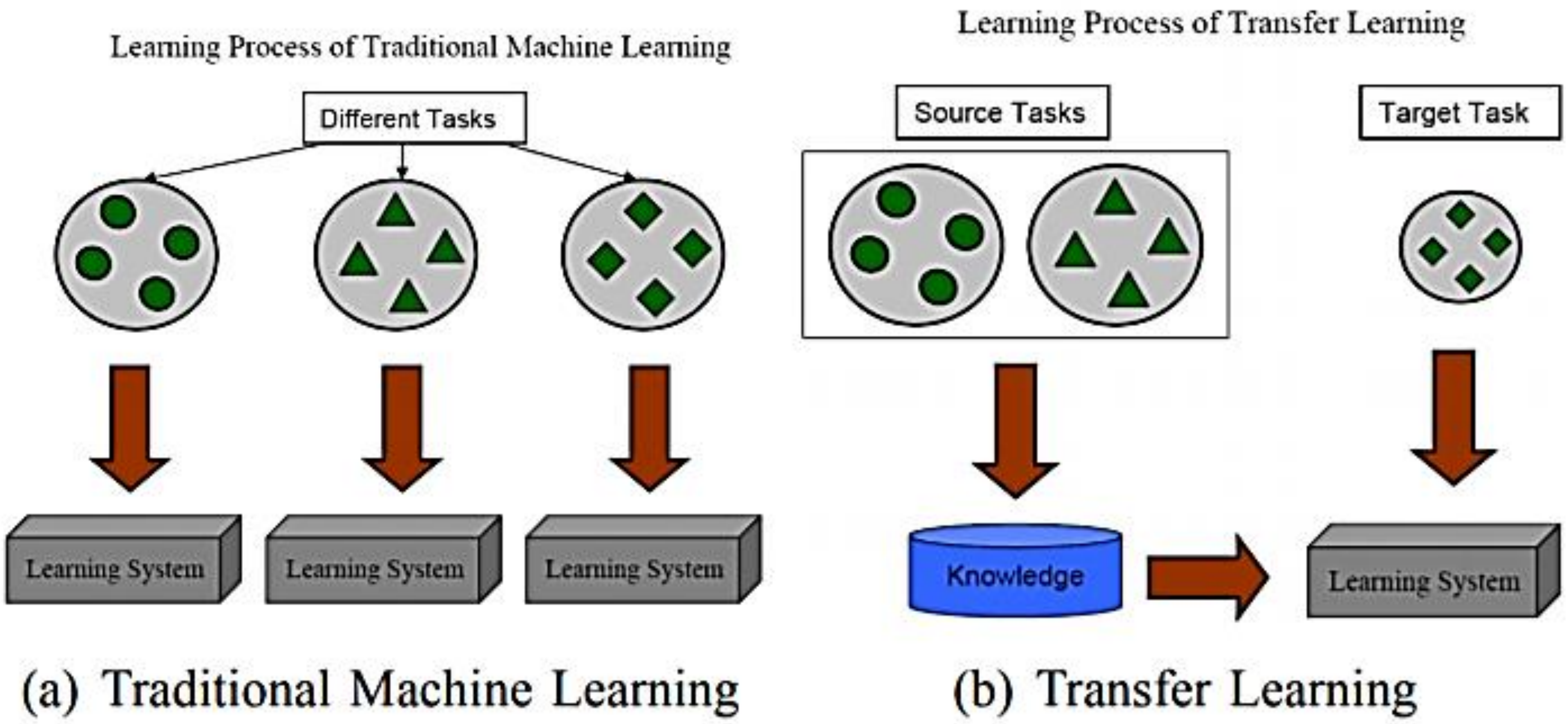
Transfer Learning

- Introduction
- Definition of TL
- Categorization of TL
  - Instance-based
    - Noninductive
    - Inductive
  - Feature-based
  - Model-based
  - Relation-based
- Heterogeneous TL
- Negative Transfer
- **TL with Deep Learning**
- Fundamental Research Issues
- Applications of TL
- References

TL with Deep Learning

- **Deep Learning**[JD92, TLB]**: Nonlinear Representations**
  - **Hierarchical** network.
  - **Disentangle** different explanatory factors of variation behind data samples.
- **Transfer Learning**[JD92, TLB]**:**
  - Doesn’t need a large **amount** of data.

TL with Deep Learning



Machine Learning and Transfer Learning (from [CSE])

Transfer Learning

- Introduction
- Definition of TL
- Categorization of TL
  - Instance-based
    - Noninductive
    - Inductive
  - Feature-based
  - Model-based
  - Relation-based
- Heterogeneous TL
- Negative Transfer
- TL with Deep Learning
- **Fundamental Research Issues**
- Applications of TL
- References

Fundamental Research Issues

- There are three research issues in TL: “what to transfer”, “how to transfer” and “when to transfer” [TLB]
    - “What to transfer” basically means to ask what knowledge across domains can be transferred to boost the generalization performance of the target domain.
    - After identifying what knowledge to transfer comes the “how to transfer” question which means how to encode the knowledge into a learning algorithm to transfer.
    - The “when to transfer” issue is to ask in which situations transfer learning should be performed or can be performed safely.

Fundamental Research Issues

- A fundamental research question behind these three issues is how to measure the “distance” between any pair of domains or tasks.
  - With the distance measure between the domains or task, we can answer the previous questions.
- A subsequent question is: what form should such a notion of distance measure be in?
  - Existing statistical measures can be used but with limits.

Transfer Learning

- Introduction
- Definition of TL
- Categorization of TL
  - Instance-based
    - Noninductive
    - Inductive
  - Feature-based
  - Model-based
  - Relation-based
- Heterogeneous TL
- Negative Transfer
- TL with Deep Learning
- Fundamental Research Issues
- **Applications of TL**
- References

Applications of TL

- Image Understanding [TLB, JO]
- Text Mining [JD92, ARX]
- Activity Recognition[JD92]
- Bioinformatics Application[ARX]
- Transportation Application[ARX]

Transfer Learning

- Introduction
- Definition of TL
- Categorization of TL
  - Instance-based
    - Noninductive
    - Inductive
  - Feature-based
  - Model-based
  - Relation-based
- Heterogeneous TL
- Negative Transfer
- TL with Deep Learning
- Fundamental Research Issues
- Applications of TL
- **References**

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Q & A

Thank you very much for your attention!

More material in
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