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Introduction to Transfer Learning

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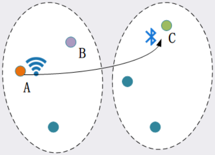
Content

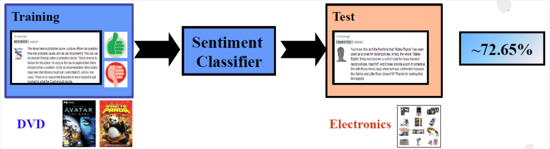
Activity Recognition: An Example

A: labeled Wi-fi $\rightarrow$ C:unlabeled Bluetooth, but how?



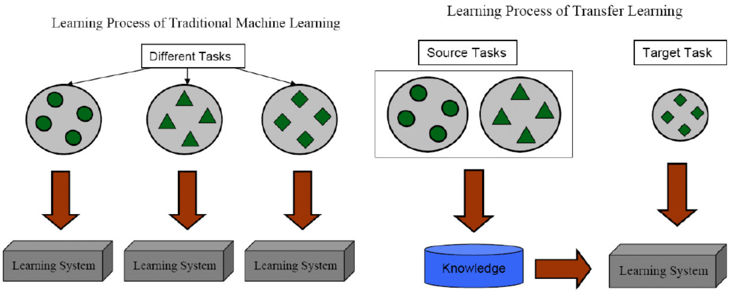
Sentiment Classification: Another Example

Only sentiments on DVD, how to obtain those on Electronics?



Basics

- Building every model from scratch is time-consuming and expensive.
- But there are many existing knowledge. Can we reuse them?



(a) Traditional Machine Learning (b) Transfer Learning

The Origin of TL

- *Thorndike* and *Woodworth* in 1901:
  how individuals **transfer** in one context to another context that share **similar** characteristics [TW01].

Common Definition

- Wikipedia: research problem in machine learning that focuses on storing knowledge gained while solving one problem and applying it to a **different** but **related** problem [wik].

Proceedings

- Data mining: ACM SIGKDD, IEEE ICDM, PKDD
- Machine learning: ICML, NIPS, ECML, AAAI, IJCAI
- Applications: ACM SIGIR, WWW, ACL, IEEE TKDE

Traditional ML Assumptions

- Training and testing samples must be in the **same** feature distributions.
- Training samples must be **enough**.

TL conditions

- Source and target domains do **not** need to be in the same distributions.
- **Less** training samples, even **none**.
- Example: getting labeled samples is time-consuming and expensive.

Basic notations

- Domain: $\boldsymbol{D} = (\mathbf{X}, P(X))$,$\mathbf{X}$: feature space, $P(X)$: marginal distribution where $\mathbf{X} = \{X_1, X_2, \cdots, X_n\}$
- Task: $\boldsymbol{T} = (Y, f(\cdot))$,$Y$: label space, $f(\cdot)$: objective predictive function.

Transfer learning

- Source domain: $\boldsymbol{D}_S = \{\mathbf{X}_S, P(X_S)\}$
- Source task: $\boldsymbol{T}_S = \{Y_S, f_S(\cdot)\}$
- Target domain: $\boldsymbol{D}_T = \{\mathbf{X}_T, P(X_T)\}$
- Target task: $\boldsymbol{T}_T = \{Y_T, f_T(\cdot)\}$
- Goal: $\min \epsilon(f_T(\mathbf{X}_T), Y_T)$
- Conditions: $\boldsymbol{D}_T \neq \boldsymbol{D}_S$ or $\boldsymbol{T}_T \neq \boldsymbol{T}_S$ with $(\boldsymbol{D}_T, \boldsymbol{D}_S, Y_T, Y_S)$ may be unknown, respectively

By Data Distribution

- Inductive TL
- Transductive TL
- Unsupervised TL

By Methodology

- Instance based TL
- Feature based TL
- Parameter/model based TL
- Relational TL

Transfer Learning Settings	Related Areas	Source Domain Labels	Target Domain Labels	Tasks
Inductive Transfer Learning	Multi-task Learning	Available	Available	Regression, Classification
	Self-taught Learning	Unavailable	Available	Regression, Classification
Transductive Transfer Learning	Domain Adaptation, Sample Selection Bias, Co-variate Shift	Available	Unavailable	Regression, Classification
Unsupervised Transfer Learning		Unavailable	Unavailable	Clustering, Dimensionality Reduction

Figure: Transfer learning settings[PY10]

Inductive transfer learning

Given $\boldsymbol{T}_S \neq \boldsymbol{T}_T$ under conditions:

- A lot of labeled $\boldsymbol{D}_S$ or
- No labeled $\boldsymbol{D}_S$

Transductive transfer learning

Given $\boldsymbol{T}_S = \boldsymbol{T}_T$ under conditions:

- $\mathbf{X}_S \neq \mathbf{X}_T$ or
- $\mathbf{X}_S = \mathbf{X}_T$ and $P(X_S) \neq P(X_T)$

Unsupervised transfer learning

Given $\boldsymbol{T}_S \neq \boldsymbol{T}_T$ under conditions:

- No labeled $\boldsymbol{D}_S$ and $\boldsymbol{D}_T$

Taxonomy
Categoried by Approaches

Instance based transfer learning
Reuse source domain: instance re-weighting and importance sampling

Feature based transfer learning
Learn good feature representation of target domain

Parameter based transfer learning
Transfer models between source and target domains

Relational transfer learning
Relationships are same in source and target domains

Deep Learning: Nonlinear Representations

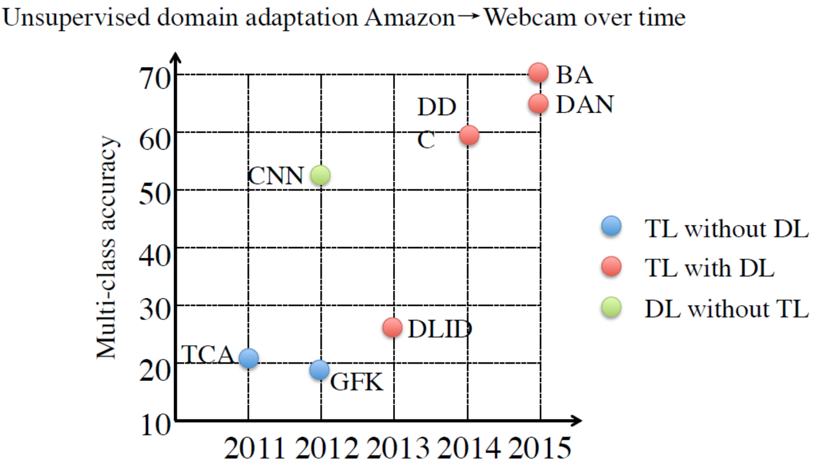
- **Hierarchical** network.
- **disentangle** different explanatory factors of variation behind data samples.

Transfer Learning: Alleviation

- Doesn't need a large **amount** of data.

Transfer Learning with Deep Learning
Benchmark

Applying transfer learning with deep learning **outperforms** directly applying Deep Learning.



Negative Transfer

Negative transfer happens when source domain data and task contribute to **reduced** performance of learning in the target domain.

Negative Transfer Conditions

- Domains are too dissimilar [RMKD05]
- Conditional Kolmogorov complexity is not related [BH03]
- Tasks are not well-related [BH03]

Transitive transfer learning [TSZY15]

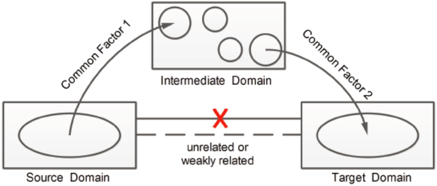


Figure: TTL tries to bridge the source and target domain using auxiliary sources

Can we transfer from existing activities domain to a different but related domain?[ZHY09]

Problem Formulation

- Labeled source activities: $\mathbf{A}_{src} = \{a_1, a_2, \cdots, a_m\}$
- Unlabeled target activities: $\mathbf{A}_{tar} = \{a_{m+1}, a_{m+2}, \cdots, a_n\}, \mathbf{A}_{src} \cap \mathbf{A}_{tar} = \emptyset$.

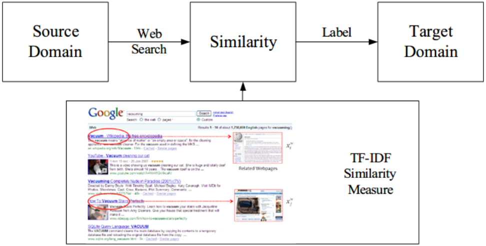


Figure: Cross domain activity recognition

Similarity Measure

What is a good similarity measure?

Maximum Mean Discrepancy [BGR+06]

- $X = \{x_1, x_2, \cdots, x_n\}, Y = \{y_1, y_2, \cdots, y_m\}$, i.i.d
- $\|\cdot\|_{\mathcal{H}}$: Reproducing Hilbert Kernel Space
- ϕ: kernel function, like Gaussian

$$MMD^2(X,Y) = \|\frac{1}{n}\sum_{i=1}^{n}\phi(x_i) - \frac{1}{m}\sum_{i=1}^{m}\phi(y_i)\|_{\mathcal{H}}^2$$

Other Measures

- Cosine similarity: $sim(X,Y) = \frac{X \cdot Y}{|X||Y|}$
- Kullback-Leibler (KL) divergence: $D_{KL}(P\|Q) = \sum_i P(i) \log \frac{P(i)}{Q(i)}$
- Jensen-Shannon divergence (JSD): let $M = \frac{1}{2}(P+Q)$, then $JSD(P\|Q) = \frac{1}{2}D_{KL}(P\|M) + \frac{1}{2}D_{KL}(Q\|M)$

Text Mining

- Unified clustering and shared knowledge transfer [DXYY07a]
- Transfered Bayes [DXYY07b]

Image Processing

- Text to image clustering [DCX^{+}08]
- Heterogeneous transfer learning [ZCL^{+}11b]

Collaborative Filtering

- Sub feature space transfer [PXY12]
- Latent feature sharing [CLY10]

Indoor Localization

- Transfer similar floors [WZZY10]
- A transfer learning framework [ZY14]

Activity Recognition

- Cross-people mobile phone based AR [ZCL$^+$11a]
- Community similarity network [LXL$^+$11]

Resources

- Open source program: `http://www.cse.ust.hk/TL/`
- *Qiang Yang*: `http://www.cs.ust.hk/~qyang/`
- *Sinno Jialin Pan*: `http://www.ntu.edu.sg/home/sinnopan/`
- *Wenyuan Dai*: `http://www.4paradigm.com/homepage.html`

Survey

- A survey on Transfer Learning [PY10].
- Transfer learning for activity recognition: A survey [CFK13].
- Transitive Transfer Learning [TSZY15].
- Fuzzy Transfer Learning: Methodology and application [SC15].

Future Work

- Reliable similarity measure
- Transfer within different algorithms
- More accurate theoretical support

Figure: The future of machine learning [Yan16]

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Q & A

Thank you for your listening