Transfer learning
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Transfer learning specifies the set of methods to convey the knowledge obtained from one domain to another one within a classification process. The data in the source domain usually have labels and those in the target domain (supposedly) do not. The aim is to avoid running the learning process over again and to eliminate the need to have labelled data for each particular new domain. For example, we have a sentiment classifier trained on movie reviews but we need to detect the sentiment of product review texts whose sentiment labels we do not know. If we use this classifier as it is, the accuracy of its answers is expected to be low. Thus, we need a method that combines the common sentiment-related knowledge in both movie and product review texts so that its performance will not be lower than its potential.
The key point in transfer learning is that the feature space and/or the probability distributions of the source and target data are different [1]. The topics or languages of the documents in the two sets might be different, for example. Event the objectives might be different such that the labels in the source and target sets may be non-overlapping.

Taxonomy:

- Instance transfer: Re-weight the features / Sample selection (Zadrozny 04 -[24])
- Feature / representation transfer: Learn new feature representations for the target using the knowledge gained from the source. (Daumé 07)
- Parameter transfer: The whole model has a set of parameters, and source and target sets have their own parameters. Assuming there is a set of shared parameters between the two, these shared parameters can be useful for knowledge transfer between the two sets. (Gao 2008) Target labels should be available.
- Relational knowledge transfer: Assuming there is a similarity in terms of the relationships in the source and target domains, the objective is to learn these relationships. [50] Target labels should be available.

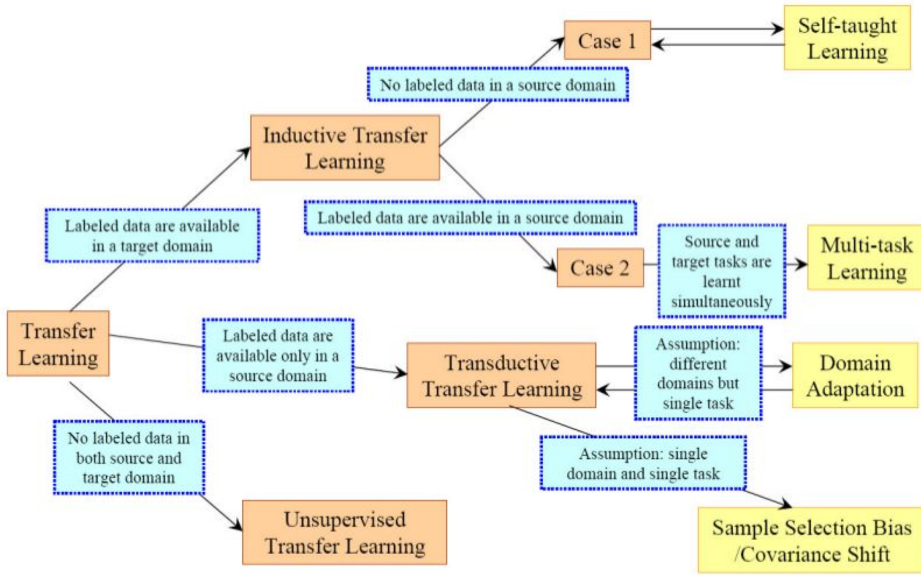

Fig. 2. An Overview of Different Settings of Transfer

(Img source: [1])

Deep learning

The source and target data is represented in such a way that features of both are reflected. The most common technique is using deep auto-encoders. [3, 4]
As a side, it is indicated that non linearity helps in avoiding feature-related losses across domains.

Available software:

(Citation numbers are from the paper [2])
Prettenhofer [91] https://github.com/pprett/bolt [7]
Zhu [146] http://www.cse.ust.hk/~yinz/ [139]
Dai [21] https://github.com/BoChen90/machine-learning-matlab/blob/master/TrAdaBoost.m [6]
Daumé [22] http://hal3.name/easyadapt.pl.gz [32]
Duan [30] https://sites.google.com/site/xyzliwen/publications/HFA_release_0315.rar [49]
Kulis [58] http://vision.cs.uml.edu/adaptation.html [18]
Qi [92] http://www.eecs.ucf.edu/~gqi/publications.html [44]
Li [64] http://www.lxduan.info/#sourcecode_hfa [67]
Gong [42] http://www-scf.usc.edu/~boqinggo/ [9]

Long [68] http://ise.thss.tsinghua.edu.cn/~mlong/ [75]
Oquab [81] http://leon.bottou.org/papers/oquab-2014 [88]
Long [69] http://ise.thss.tsinghua.edu.cn/~mlong/ [75]
Other transfer learning code http://www.cse.ust.hk/TL/ [115]

Alternative approaches:

- Semi-supervised or weakly supervised learning
- Distant supervision

References

[1] Pan, Sinno Jialin, and Qiang Yang. "A survey on transfer learning." *IEEE Transactions on knowledge and data engineering* 22.10 (2010): 1345-1359.
[2] Weiss, Karl, Taghi M. Khoshgoftaar, and DingDing Wang. "A survey of transfer learning." *Journal of Big Data* 3.1 (2016): 1-40.
[3] Glorot, Xavier, Antoine Bordes, and Yoshua Bengio. "Domain adaptation for large-scale sentiment classification: A deep learning approach." *Proceedings of the 28th International Conference on Machine Learning (ICML-11)*. 2011.
[4] Zhuang, Fuzhen, et al. "Supervised representation learning: Transfer learning with deep autoencoders." *Int. Joint Conf. Artif. Intell*. 2015.