

Learning from Partially Labeled Data

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Abstract.

Providing sufficient labeled training data in many application domains is a laborious and costly task. Designing models that can learn from partially labeled data, or leveraging labeled data in one domain and unlabeled data in a different but related domain is of great interest in many applications. In particular, in this context one can refer to semi-supervised modelling, transfer learning, domain adaptation and multi-view learning among others. There are several possibilities for designing such models ranging from shallow to deep models. These type of models have received increasing interest due to their successful applications in real-life problems. This paper provides a brief overview of recent techniques in learning from partially labeled data.

1 Introduction

In many application domains one encounters limited labeled training data while unlabeled data are more easily generated and available. The literature has witnessed several attempts in overcoming the challenges of learning from partially labeled datasets by proposing models that can leverage available labeled or unlabeled data in different domains. The semi-supervised learning, domain adaptation, multi-view learning are among existing proposed models.

Semi-supervised models use both labeled and unlabeled data points in the learning process. To this end, one incorporates the labels/unlabeled data in the learning process to enhance the clustering/classification performance. Usually both labeled and unlabeled data are from one domain and are drawn from the same distribution. However there are several cases in which they are drawn from different distribution, they have different feature dimensions. It is also possible that they are drawn from two different but related domains. One can further generalize this pattern and consider the case that the training and test data do not exhibit the same distribution, same feature domains or their statistical properties change over time. The data might also have been described using different representations, views or modalities. In all these cases, many classical machine learning algorithms fail to provide the desired classification performance. Therefore, addressing these challenging problems by designing suitable techniques and models has recently attracted many researchers. In what follows we will give an overview of some of the recent existing techniques that are used for learning from

partially labeled data with above mentioned level of complexity. In particular, in Section 2, a brief overview of existing semi-supervised modelling techniques is provided. Domain adaptation methodologies are discussed in Section 3. Multi-view learning methodologies are given in section 4.

2 Semi-supervised learning

Traditionally, there are two different types of tasks in machine learning, namely supervised and unsupervised. In supervised learning all the training samples are labeled and one tries to learn a right mapping from the given input to the desired output. On the other hand, in unsupervised learning the training samples are all unlabeled and the task is to for instance group or cluster the given data and find the underlying patterns of the data. Semi-supervised learning (SSL) lies between supervised and unsupervised learning where it aims at learning from both labeled and unlabeled data, see Fig. 1. Learning from few labeled and a large number of unlabeled training data is directly relevant to several practical problems where it is expensive to produce labeled data. Semi-supervised learning (SSL) is one of the modelling approaches that is able to cope with the limited training data and has already shown its importance in many application domains including automatic classification of web pages, medical images analysis, traffic or climate data, biomedical signals among others. In this type of learning one can benefit from different type of partial supervision.

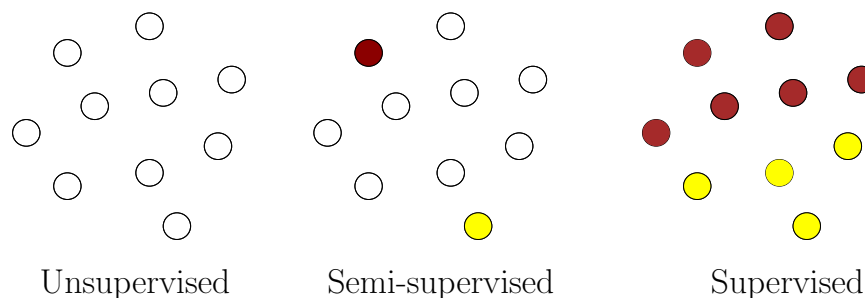


Fig. 1: Supervision Spectrum

For instance, there might be constraints on the data points such as having the same target or not, or simply the target values for only some of the training samples are given. In general there are two views on semi-supervised modeling. In the first view the SSL is seen as unsupervised learning guided by constraints and in the second view, SSL is considered as supervised learning with additional information on the distribution of the examples [1, 2, 3, 4, 5, 6]. The semi-supervised learning can be classified into two categories, i.e. transductive and inductive learning [7]. In transductive learning the labels for a specified set of test data are predicted. In inductive learning one learns a decision function from a training data for future unobserved test instances. One can further

categorize the semi-supervised inductive learning into semi-supervised clustering and classification [2]. In semi-supervised clustering the task is to exploit labeled data to adjust the cluster memberships of the unlabeled data. In contrary, semi-supervised classification uses both unlabeled and labeled data to obtain a better predictions and classification accuracy on unseen test data points [2].

Traditionally, in semi-supervised techniques, a classifier is first trained using the available labeled data points and then the classified unlabeled data with the highest confidence scores are added incrementally to the training set and the process is repeated until the convergence criteria is met [8]. Some of the successful semi-supervised models that have been proposed in the literature are for instance, the Laplacian support vector machine (LapSVM) [7] with manifold regularization, local spline regression for semi-supervised classification [9], A label propagation [10], nonlinear embedding in deep multi-layer architectures [11] and Semi-Supervised Kernel spectral clustering [2]. The design of many existing SSL models benefits from one of the cluster assumption or manifold assumption. In the former, the decision boundary between classes should lie in the lower density region of the space. The latter assumes that the target function should change smoothly along the tangent direction. It should be noted that most of the graph based models perform transductive learning. However, LapSVM is one of them with a data-dependent geometric regularization which has the out-of-sample extension property and therefore is able to perform inductive inference.

The authors in [2] formulated a regularized Kernel Spectral Clustering (KSC) which can be operated for both semi-supervised classification and clustering. The KSC which is a completely unsupervised algorithm is used as the core model and the available labeled data is incorporated to this model via adding a regularization term to the cost function of the KSC formulation. Thanks to the added regularization term, the model clustering scores are adjusted to be as close as possible to the desired labels. The model is then obtained by solving a linear system of equations in the dual. Extension of this model to analyze streaming data in an online fashion has been proposed in [12].

Nowadays, deep learning has shown its great power in several learning tasks. When training deep neural networks, samples with qualified labels are quite important, due to their over-fitting essence. However, there are many applications which contain vast amount of unlabelled data. For example, in computer assisted diagnosis tasks, there could be many medical images, but the labels, especially accurate masks, need very heavy human consumption. Thus, learning from partially labeled data becomes attractive for training deep neural networks for those tasks. There are different ways to use unlabeled data for training neural networks. The unlabeled data could pre-train parts of the neural networks to coincide with some expectations, e.g., sparse structure or similarity in latent space. In those methods, unlabeled data are used in a unsupervised manner [13, 14]. There are various methodologies for giving labels to unlabeled data. In [15], a surrogate class is generated by automatically generating samples from unlabeled data. In [16, 17, 18, 19], pseudo-labels are given to the unlabeled data by links between labeled and unlabeled samples, which could be represented by

graph or manifold.

In addition to predicting and assigning labels to unlabeled data and transferring the training task to supervised one, designing loss/target functions for those unlabeled data is another efficient way. The design could be rooted in underlying guesses, observations, or reasonable assumptions. For example, the output distribution of a neural network for labeled and unlabeled data should be the same [20]; the entropy should be minimized not only on labeled data but also on the unlabeled ones [21]; all the data, no matter there are labels or not, could be embedded in the same manifold [22]; a generative model could be trained on unlabeled data and be mixed up with labelled data [23]. Among many deep semi-supervised methods, the ladder net, proposed by [24], is a representative work and has achieved very good performance. The idea of ladder net appeared first in unsupervised learning [25] and the basic structure is an auto-encoder, which is to remove noise by minimizing the difference of the original input and its reconstruction. In semi-supervised learning, the label from the labeled and the structure in all data are used together in the ladder net such that clean features coinciding with prior expectations could be learned [24].

3 Domain adaptation

In many practical machine learning problems the statistical properties of the data change from one domain to another. This domain shifts brings new challenges for classical machine learning algorithms which are designed based on the assumption stationary data. Therefore the need for designing models that can leverage the information of the labeled data in one domain to better classify unseen data in a target domain is highly desirable. To this end, domain adaptation based models are proposed in the literature. In both domain adaption and semi-supervised learning one tries to leverage labeled data to improve the model generalization performance on the unseen unlabeled data. However, in domain adaptation there are extra assumptions, i.e. one is dealing with two domains which exhibit different distributions and/or there is a feature dimension mismatch. In case one can ignore these assumptions, then the source and target domain can provide the labeled and unlabeled data to be used by semi-supervised models.

There are three main scenarios one can consider for domain adaption problems which differ in the information considered for the target task. In unsupervised domain adaptation, one learns from a set containing labeled, unlabeled source instances and unlabeled target instances, i.e the labeled information from the target domain is not taken into account. In supervised domain adaptation, all the instances considered are labeled. In the semi-supervised setting, one learns from labeled source instances as well as a small fraction of the target labeled instances [26]. The main two types of domain adaptation problems that are addressed in the literature are homogeneous and heterogeneous domain adaptation. In the homogeneous domain adaptation, the feature representation for the source and target domains is the same, i.e. $\mathcal{X}_s = \mathcal{X}_t$ but the marginal probabil-

ity distributions are not the same i.e. $P(\mathcal{X}_s) \neq P(\mathcal{X}_t)$. However heterogeneous domain adaptation is more challenging since the distributions, feature domains and dimensions in source and target are different. The literature have witnessed several domain adaptation methodologies for addressing both homogeneous and heterogeneous data. The two main categories are models with shallow and deep architectures. In what follows we give a brief overview of some of the successful shallow domain adaptation methods.

In shallow and traditional models there are three major directions of works proposed in the literature for domain adaptation problems including instance re-weighting methods [27, 28, 29] and feature transformation [30, 31]. In the sample reweighting approach, one assigns sample-dependent weights to the training data with the aim of minimizing the distribution discrepancy between the source and target data points in the re-weighted space [27]. In practice one usually can use the density ratio between the probability densities of the two domains to estimate the sample dependent weights. Another main approach in domain adaptation is to learn a domain-invariant feature representation for both source and target domains. Several successful feature transformation methods are proposed in the literature. The authors in [30] introduced the Transfer Component Analysis (TCA) in order to learn common latent features having the same marginal distribution across the source and target domains. The Structural Correspondence Learning method proposed in [31] learns a common feature space by identifying correspondence among features from different domains. A domain adaptation approach that uses the correlation subspace as a joint representation of the source and target data is introduced in [32].

Often in many domain adaptation problems, side information in the form of correspondence (paired) instances are available across domains, see Fig. 2. In this case, the instance similarity constraints between domains, can be used to enhance the generalization performance of the model [33]. A Regularized Semi-Paired Kernel Canonical Correlation Analysis (RSP-KCCA) model is introduced in [26] for learning a new representation of the data for the sake of the domain adaptation problem. This model also belongs to the family of feature transformation methods. The corresponding optimization problem is formulated in the primal-dual Least Squares Support Vector Machines setting where side information are incorporated through proper regularization terms. A new representation of both source and target data sets is learnt by solving a linear system of equations in the dual. The model seamlessly integrates unlabeled, labeled, paired and unpaired instances and can be employed in unsupervised, semi-supervised as well as supervised fashions.

Other types of domain adaptation models that have recently gained attentions poses deeper architectures and are based on artificial neural-networks. Within this category of models one can refer to learning representations using the marginalized stacked denoising autoencoders (mSDA) [34], adjusting the the pre-trained networks to the new task by fine-tuning [35, 36, 37], interpolating between domains [38] and cross-domain neural-kernel networks [39].

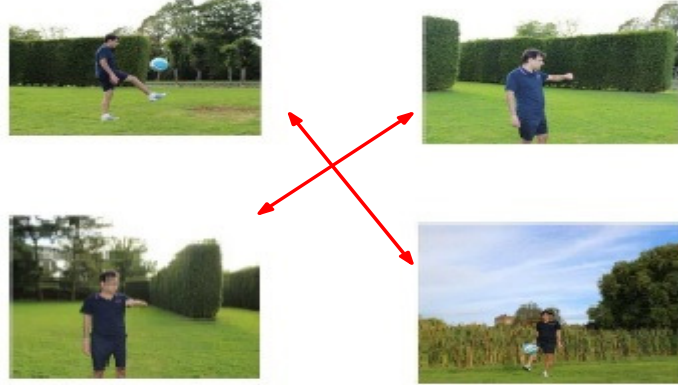


Fig. 2: Example of labeled paired instances [26].

4 Multi-view learning

The success of learning from partially labelled data relies on the full use of the links between labelled and unlabelled data. One interesting and effective way is multi-view learning, which was first proposed by [40]. Its basic assumption is that labeled and unlabeled data share similarity in different views. The original idea of multi-view learning, called co-training [40], is to learn several weak classifiers based on labeled data but from multiple views and then bootstrap the weak classifiers by unlabeled data. Later on, the idea of co-training has been theoretically analyzed in [41, 42] and successfully applied in other tasks, e.g., spectral clustering [43] [44]. Another way of using multi-view data is to design a regularization term that could capture the joint prior knowledge. In this direction, [45] is a representative method that applies kernel canonical correlation analysis [46] in support vector machines to model the similarity in a common latent space. Establishing a co-regularization term for multiple views is applicable and effective for many tasks. For example, [46] designed a regularization term from manifold-based ensemble learning; the multi-view version of the Hessian regularization method [47] achieves promising performance in image annotation; the application on graph-oriented method could be found in [48, 49, 50].

Here we list multi-view learning as a category of learning from partially labeled data. But this idea is actually applicable for many applications, no matter in supervised, semi-supervised, or unsupervised tasks. For example, the idea of co-regularization can be used in unsupervised learning task [51] when there exists a good common base manifold. In the person re-identification problem, different cameras provide multi-view for the same person and multi-view learning that considers different views simultaneously is helpful [52, 53, 54]

5 Conclusions

We have briefly reviewed several existing approaches in connection to learning from partially labeled data. The covered approaches range from shallow models to deep architectures in the context of semi-supervised learning, domain adaptation and multi-view learning.

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