Asymmetric Heterogeneous Transfer Learning: A Survey

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Abstract: One of the main prerequisites in most machine learning and data mining tasks is that all available data originates from the same domain. In practice, we often can't meet this requirement due to poor quality, unavailable data or missing data attributes (new task, e.g. cold-start problem). A possible solution can be the combination of data from different domains represented by different feature spaces, which relate to the same task. We can also transfer the knowledge from a different but related task that has been learned already. Such a solution is called transfer learning and it is very helpful in cases where collecting data is expensive, difficult or impossible. This overview focuses on the current progress in the new and unique area of transfer learning - asymmetric heterogeneous transfer learning. This type of transfer learning considers the same task solved using data from different feature spaces. Through suitable mappings between these different feature spaces we can get more data for solving data mining tasks. We discuss approaches and methods for solving this type of transfer learning tasks. Furthermore, we mention the most used metrics and the possibility of using metric or similarity learning.

1 INTRODUCTION

It can happen that while solving a data mining task in some domain of interest we will have data available from different feature spaces. Different feature spaces are two spaces, which are represented by different features. These spaces can originate from other domains and we can divide them into source (usually contains data used for the training of the model) and target feature space (contains data used for testing of the model). We can also divide the domains into source and target to distinguish where the data comes from. Common machine learning methods assume that the distributions of the individual attributes in the used data are the same. However, in practice these assumptions are often incorrect. Let us imagine that our task is object classification, where our domain is represented by several pictures. Two images of the same object may be of different dimensions of features because of different resolutions, illuminations or tilts. A different task can be cross-lingual document classification. For example labeled English documents are widely available, but labeled Chinese documents are much harder to obtain. These documents, English and Chinese, do not share the same feature representation. Transfer learning can use natural correspondence between feature spaces in order to create an automated learner for Chinese documents. Transfer learning allows the domains, tasks and distributions used in solving tasks to be different (Zheng, 2015).

In a broader context transfer learning can be regarded as a group of methods which fall into the category of semantic-meaning based methods for cross-domain data fusion. Data fusion consists of techniques for integration of knowledge from various data in a machine learning and data mining task (Zheng, 2015). Transfer learning concerns itself with knowledge fusion rather than schema mapping and data merging, which are more specific for traditional data fusion and data integration being pursued by the database community (Zheng, 2015; Bleiholder and Naumann, 2009). Many terms exist for transfer learning, within this work you can also come across a related term - domain adaptation (Pan and Yang, 2009). Domain adaptation is focused on the development of learning algorithms, which can be easily transferred from one domain to another (Daumé III, 2009).

A general overview of transfer learning is given in (Pan and Yang, 2009) and the newest survey was introduced in (Weiss et al., 2016). The main motivation, which is also the reason that transfer learning methods are popular, is the automatization of mapping processes, saving of time and human resources, the possibility of solving tasks without knowledge of

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the domain, increasing usability of poor data, which would be unusable on its own and often also the usability of data from unused database structures.

In this survey we focus on the diversity of data from different feature spaces in the same domain of interest. We search for suitable mappings between this data, which will maintain or decrease the error of the predictive or classification model. In practice, the mapping of data is often solved manually, but in some cases this approach poses a combinatorial problem and almost always requires the presence of a domain expert. In the ideal case it would be beneficial to find such an automatic mapping, which would enable us to map the data between source and target feature spaces in both directions. This research area is called heterogeneous transfer learning and its position in the field of transfer learning can be seen in Figure 1.

Heterogeneous transfer learning can be perceived as a type of transductive learning. Transductive learning assumes that the source and target domains are different. The domain consists of two components: a feature space χ and a marginal probability distribution $P(X)$, where $X = x_1, ..., x_2 \in \chi$ (Pan and Yang, 2009). Heterogeneous transfer learning is proposed to handle the cases where the task is the same, but the source and target feature spaces are different (Pan and Yang, 2009). This difference can be that the marginal probability distributions of the data are different, but the feature spaces between source and target domains are the same. Transductive learning also assumes that we have labeled source data and unlabeled target data, but heterogeneous transfer learning is able to work with different combinations of labeled and unlabeled data which will be demonstrated on examples in Section 2. In this paper we focus on feature-based heterogeneous transfer learning, which stems from the assumption that the feature spaces between domains are different and searches for ways of mapping this dissimilar data. By difference we understand different distributions, representations and dimensionality of data. Heterogeneous transfer learning is a relatively new field of research and finds an application in such domains as text classification, image recognition, activity recognition, defect prediction etc.

There has been a large amount of work focusing on transfer learning in machine learning literature (See an overview by (Weiss et al., 2016)). However, in this survey article we give an overview of asymmetric heterogeneous transfer learning methods mainly used in machine learning and data mining areas. This survey does not provide an experimental comparison of the individual methods. Most of the methods in the surveyed papers are domain or task specific, thus they reach the best performance on specific datasets. This makes it impossible to provide a quality comparative analysis on the same datasets. An open-source repository of implemented solutions from each paper would be helpful, but unfortunately this is not available. We hope to provide a useful survey for the machine learning and data mining community.

The survey is organized as follows. In Section 2 you can find an explanation of this problem along with the prerequisites for the problem of transfer learning between different feature spaces. Section 2.1 briefly describes the solution based on common feature space. In section 2.2 we explain the available methods in more detail. In Section 3 we introduce the reader to the most used feature mappings in the field of transfer learning. In the last Section 4 we bring a brief summary of this survey and possible challenges, which we would like to address in the future.

2 HETEROGENEOUS TRANSFER LEARNING

In Figure 2 (altered figure from (Weiss et al., 2016)) we can see two approaches to the transformation of data on a feature-based level, which are addressed by different feature spaces. By transformation we understand operations (e.g. translation, scaling, etc.) which have to be done for mapping of different feature spaces. One of these is symmetric transformation (Figure 2.a). Symmetric transformation transforms the source and target feature spaces into a common latent feature space in order to unify the input spaces of the domains. The second approach is asymmetric transformation (Figure 2.b), which transforms source feature space to the target feature space. Some methods presented in Section 2.2 perform the transformation in the opposite direction from the target domain to the source domain. Some proposed methods are usable in both directions. All presented approaches in Section 2.2 are based on features (feature-based) (Pan and Yang, 2009).

We consider two datasets as a running example in this paper (shown on Figure 3). The data in these datasets originate from different source and target domains with different feature spaces. The datasets consist of a different feature representation, distribution, scale, and density of data. Relations which connect the datasets can exist between different feature spaces, because the source and target domains must be related in some way. These connections can be called correspondences among features. The discovery of as much common information as possible from these different datasets is one of the problems in data mining research. Thus, we are looking for suitable

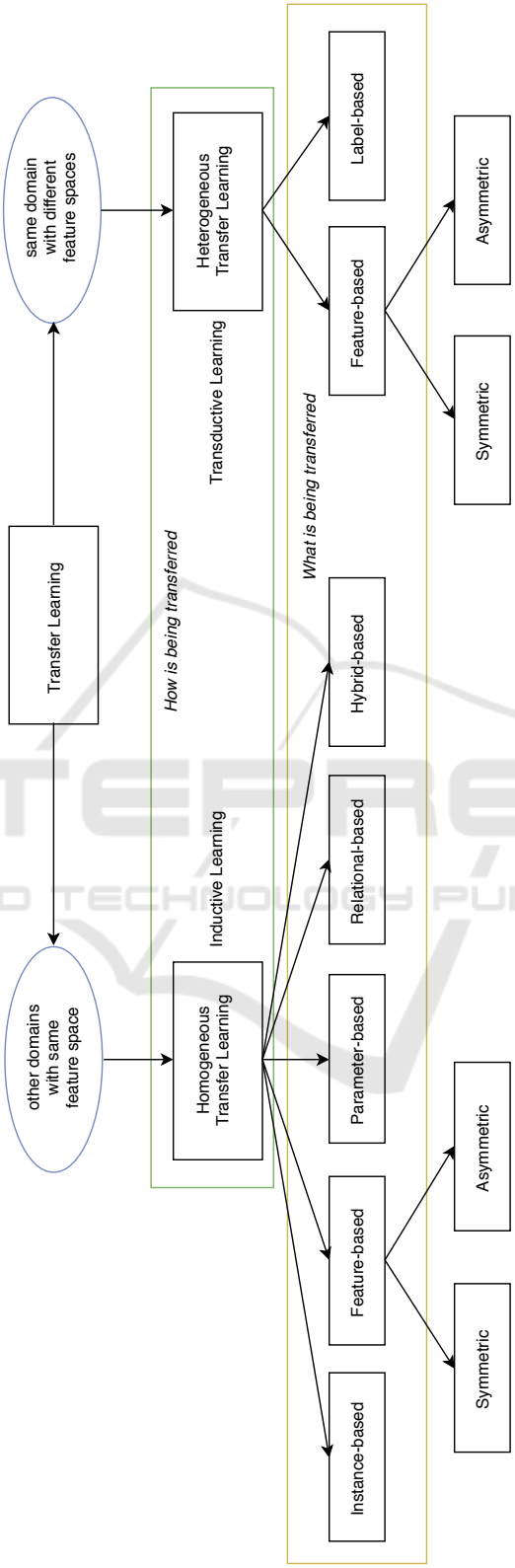


Figure 1: A hierarchical overview of different transfer learning approaches.

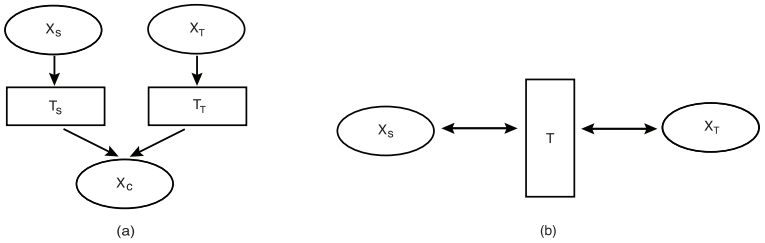


Figure 2: (a) Symmetric transformation mapping T_S and T_T of the source X_S and target X_T domains into a common latent feature space. (b) Asymmetric transformation mapping T_S of the source domain X_S to target domain X_T or vice versa from target X_T to source X_S domain.

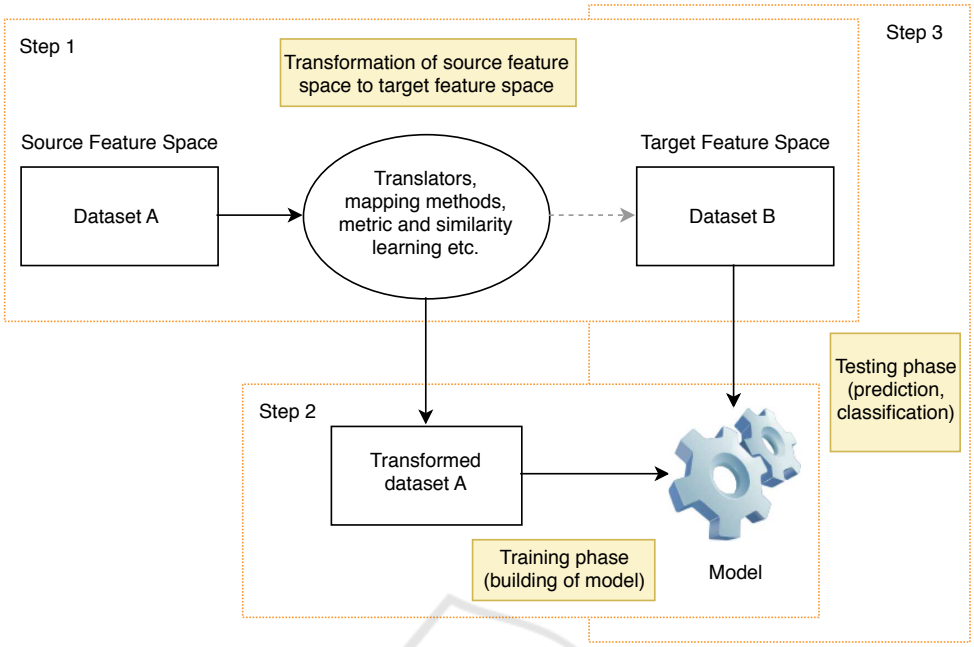
mapping functions for individual features from different feature spaces. In the ideal scenario, we are looking for mapping in both directions, which would be more general and would find a wide range of application.

2.1 Symmetric Feature-based Approach

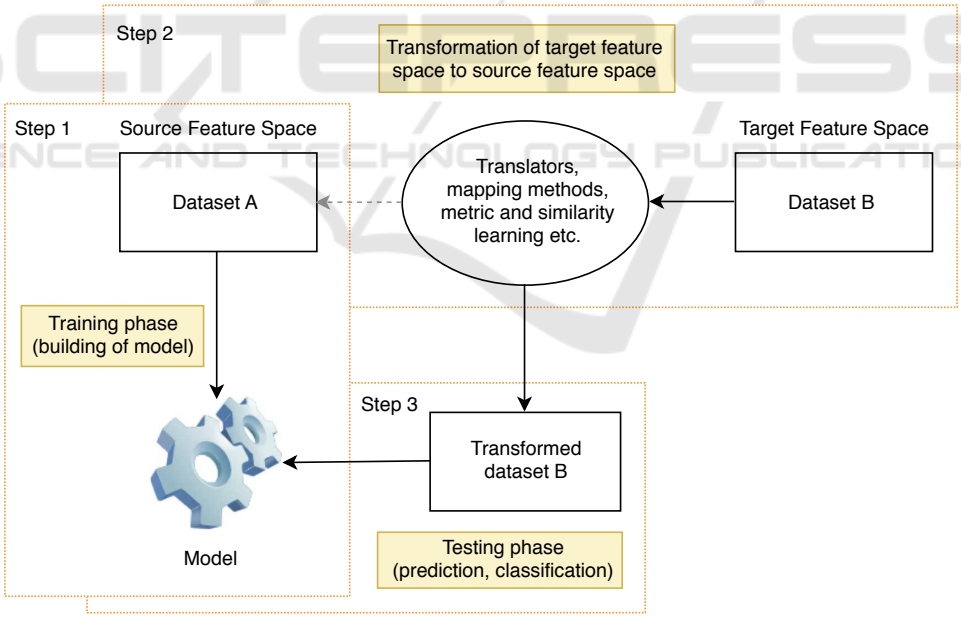
Most existing heterogeneous transfer learning methods assume that both source and target data can be represented by a common homogeneous feature space, called latent feature space. Thus, we are looking for transformation mappings T_S and T_T to transform source domain data X_S and target domain data X_T to a new common latent feature space X_C as is shown in Figure 2 (Shi et al., 2010; Prettenhofer and Stein, 2010; Wang and Mahadevan, 2011; Duan et al., 2012). There exist a lot of tasks in the natural language processing area. (Blitzer et al., 2006) introduce structural correspondence learning (SCL) to automatically induce correspondences among features from different domains. SCL is based on the correlation between certain pivot features. Pivot features are features which behave in the same way for discriminative learning (e.g. classification) in both domains. These features have the same semantic meaning in both domains and are used to learn a mapping from the different feature spaces to common latent feature space. (Pan et al., 2008) learn a common latent feature space with low dimensionality. This common latent space is learned using a new dimensionality reduction method called Maximum Mean Discrepancy Embedding. Data from related but different domains is projected onto this common latent feature space. (Daumé III, 2009) transform the source and target features into a higher dimensional representation with source, target and common components. They also introduce an extension to this method which also works for unlabeled data (Daumé III et al., 2010). (Shi et al., 2010) propose the Heterogeneous Spectral Mapping (HeMap) method. The main idea of HeMap is to find a common latent feature space for two heterogeneous tasks. A spectral mapping of the source and target feature spaces into a common latent feature space is designed. A spectral mapping is designed as an optimization task that maintains the original structure of the data while minimizing the difference between the two domains. This mapping adopts linear approaches such as rotation, scaling, permutation of row vectors and column vectors, etc. to find a common latent feature space. (Pan et al., 2008) introduce Transfer Component Analysis for dimensionality reduction of features in a common latent space. A kernel-based feature mapping method has been introduced by (Zhong et al., 2009). This method maps the marginal distribution of data from different source and target domains into common kernel space. A lot of methods for the solution of the common latent feature space problem exist. We are not going to concern ourselves with them any further in this work, because we focus on asymmetric approaches.

2.2 Asymmetric Feature-based Approach

Asymmetric transformation is perceived as a new and unique approach alternative to symmetric transformation. It consists of finding transformations T_S, which would enable us to map source domain data X_S to target domain data X_T with different feature spaces (Kulis et al., 2011; Dai et al., 2008). In practice we mostly encounter this version of the problem: we have data from a source domain, which we map to data from a target domain using various techniques. After that we train a model (Figure 3 a). We can also encounter a scenario where we have source and target data from the same domain, on which we trained a very good model. This model is successfully applied in production. However, due to various reasons, the target feature space changed and our model became unable to react to the new data. In the case that we are not able to modify the model, we have to find an ideal mapping of target data to source while making sure that the error of the model doesn't change (Figure 3 b). This approach poses a big challenge in the research area.



(a)



(b)

Figure 3: There are two approaches in asymmetric transfer learning shown on (a) and (b). (a): Step 1 consists of mapping dataset A to dataset B by using mapping methods. Step 2 consists of training the model based on data from the transformed dataset A, step 3 contains the phase where we test the model on dataset B from target feature space. (b): Step 1 consists of the training of the model based on data from dataset A from source feature space. In Step 2 we are looking for a mapping from dataset B to dataset A. Step 3 shows the testing of the model based on transformed dataset B.

2.3 Overview of Presented Solutions

Asymmetric heterogeneous transfer learning finds application in several practical domains, where mainly methods of machine learning are employed. In this section we will introduce several basic research approaches to solving tasks related to:

- computer vision – image classification;
- cross-language classification;
- cross-project defect prediction;
- activity recognition.

We start with the assumption that we have different source and target feature spaces, but the same task, as shown on Figure 3. However, if we also had a different task, we would first make use of the methods of transfer between feature spaces followed by methods of homogeneous transfer learning for the transfer of knowledge between tasks (domains).

(Kulis et al., 2011) solved the problem of domain adaptation for transferring object models from one dataset to another by introducing a novel approach in computer vision. The main idea is to learn an asymmetric non-linear transformation that maps data from one domain to another domain using supervised data from both domains. The input consists of pairs of inter-domain examples that are known to be semantically similar or dissimilar. This approach can also be used in the case that some classes in the target domain have missing labels. (Kulis et al., 2011) aims to generalize the model of (Saenko et al., 2010) in his paper, which makes use of symmetric transformations. The new approach of (Kulis et al., 2011) was called Asymmetric Regularized Cross-domain transformation, shortly ARC-t. ARC-t shows how a general formulation for the transfer learning problem can be applied in kernel space, resulting in non-linear transformations. The transformation matrix is learned in a non-linear Gaussian RBF kernel space. The resulting algorithm is based on squared Frobenius regularization (Kulis et al., 2013) and similarity constraints. Similarity constraints are created for all pairs of data in the same class by using a similarity function. It helps us to decide which pairs of data are similar and dissimilar. During testing the method showed certain advantages compared to existing baseline approaches such as k-nearest neighbors, SVM, domain and cross-domain metric learnings and the feature augmentation method proposed by (Daumé III, 2009). The main idea of feature augmentation is to duplicate features in order to capture differences among domains. This method is briefly discussed in Section 2.1.

(Zhou et al., 2014b) proposed a domain adaptation method where data originates from heterogeneous feature spaces of different dimensions. The method includes a transformation matrix to map the weight vector of classifiers learned from source domain to target domain. This method works if the following requirements are met: sparse feature representation and class-invariant transformation. Sparse feature representation means that a feature in one domain can be represented by only several features in a different domain. The feature mapping across these domains is linear. Class-invariant transformation means that the feature mapping of some feature is invariant to different classes. To make the learning of a heterogeneous domain possible, the transformation matrix has to learn the similarity between source and target domain data. This data can be transformed from source feature space to target feature space and equivalently vice versa. (Zhou et al., 2014b) used the scheme - the Error Correcting Output Codes (ECOC) to generate binary classifiers for the multi-class classification problem (Dietterich and Bakiri, 1995). With ECOC, their solution, called Sparse Heterogeneous Feature Representation (SHFR), can learn a transformation matrix. Part of the learning process of the transformation matrix is the adoption of a multi-task learning method based on (Ando and Zhang, 2005). The multi-task learning is based on learning more task simultaneously (Pan and Yang, 2009). SHFR method (also in combination with ECOC) was tested against DAMA (Dai et al., 2008), ARC-t (Kulis et al., 2011) and HFA (Duan et al., 2012).

We are further going to state several examples from practice. Heterogeneous transfer learning finds numerous applications in the area of activity recognition. In this area the activities of daily living are monitored through diverse sensors. This monitoring is a crucial step in the future of elderly people care. There is motivation to use existing data from other houses in order to learn the parameters of the model for a new house. The reason is that activity recognition models often rely on labeled examples of activities for learning, which are missing in a new house. Activity recognition and discovery models usually include information based on structural, temporal and also spatial features of the activities (Cook et al., 2013; Rashidi and Cook, 2010).

For the activity recognition task, (van Kasteren et al., 2010; van Kasteren et al., 2008) introduce a method in which sensors in the source domain are mapped to similar sensors in the target domain. Semi-supervised learning is used for learning parameters of the Hidden Markov Model (HMM). They propose a number of manual mapping strategies for mapping sensors between different houses: intersect, duplicate, union.

(Rashidi and Cook, 2010) also map sensors from source to target domain based on location or function. Their method is called Multi Home Transfer Learning (MHTL). MHTL composes of 3 phases – activity extraction (output heads to activity templates), mapping and label assignment. The activity model consists of various features from sensors, such as structural, spatial and temporal. Their method is a good example of the utilization of meta-features. Meta-features are common for all data. It is a kind of mapping allowing us to have a single common feature space that can be used for all houses (van Kasteren et al., 2010). In (Rashidi and Cook, 2010) meta-features are first manually introduced into the feature space (for every source-target pair). Then this feature space is automatically mapped from the source to target domain. Other works using meta-features are (Blanke and Schiele, 2010; van Kasteren et al., 2010).

(Harel and Mannor, 2011) designed a Multiple Outlook Mapping algorithm (MOMAP). MOMAP computes optimal affine mappings from different source feature spaces (in their terminology outlooks) to a target feature space by matching moments of empirical distributions. These spaces are not related through corresponding instances, but only through the common task. The optimal affine mapping is a function of geometric projection which maps the points lying on the same line onto one common point or to the same number of other points. Affine mapping preserves the division ratio (Nomizu and Sasaki, 1995). In the MOMAP algorithm affine mapping is represented by translation and rotation. The mapping is done by matching moments of empirical distributions. The empirical distribution function is associated with an empirical measure of samples. Empirical measure means random measure realization of a sequence of random variables. The moments are quantiles from the empirical distribution function (van der Vaart, 2000). Before mapping in the MOMAP algorithm, the scaling of features of all spaces is required. The scaling aims to normalize the features of all spaces to the same range. Then the mapping is performed by translating the means of each class to zero. Next, the rotation of the classes to fit each other is done by a rotation matrix. Finally, we have to translate the means of the mapped space to the final space. The framework performance is demonstrated on activity recognition data.

A lot of transfer learning methods solve situations where the difference between the source and target domains is caused mainly by differences in the marginal probability distributions of the domains (Rashidi and Cook, 2010; Blitzer et al., 2007; Blitzer et al., 2006). By marginal probability distribution we mean probability distribution of the features contained in the subset of a collection of random features.

(Feuz and Cook, 2015) propose a novel heterogeneous transfer learning technique called Feature-Space Remapping (FSR). FSR can handle the different feature spaces without the use of co-occurrence data (correlated data), as is shown for example in (Dai et al., 2008). FSR maps the data to a different feature space using part of labeled data from the target domain to infer relations to the source domain. FSR requires a one time manual specification of meta-features and then can be applied to map multiple source and target domains. (Feuz and Cook, 2015) map the features from target feature space to different source feature space. To achieve the feature mapping, they learn a mapping from each dimension in the target feature space to a corresponding dimension in the source feature space. FSR computes the average similarity between the source and target meta-feature values for each pair between features from source and target feature spaces. The similarity is calculated between two meta-features as the absolute value of the difference between meta-feature values divided by the maximum possible difference between the meta-features. As a product we get many-to-one mapping.

One of the typical tasks of transfer learning is language transformation between multilingual documents or web pages, specifically the transformation from one language to another. This task can be solved by using automatic translators mentioned in (Wei and Pal, 2010). Transfer learning is aiming to solve the task without these tools, only using the transfer of knowledge between related feature spaces. Most methods learn a feature mapping between source and target domain based on data correspondences (Kulis et al., 2011; Dai et al., 2008). Correspondence means that there exists some relationships between data from different feature spaces. (Zhou et al., 2014a) present a hybrid heterogeneous transfer learning (HHTL) framework. HHTL consists of deep learning which learns a feature mapping from the target domain to the source domain. HHTL simultaneously corrects the data bias on the mapped feature space. This framework was tested on multilingual text mining tasks.

(Dai et al., 2008) propose to learn feature mapping based on the construction of feature correspondences between different feature spaces. This construction is called translator in (Dai et al., 2008). In this work the language model is used. The language model is a probability distribution over sequences of words (Lafferty and Zhai, 2001). The language model links the class labels to the features in the source

spaces and turns their translation to features in the target spaces. This novel framework is called translated learning (TLRisk). The main idea of translated learning is to translate all the data from source feature space into a target feature space. We assume there is no correspondence between instances in these different feature spaces. The language model proposed by (Dai et al., 2008) consists of feature translation and nearest neighbor learning. We can imagine this model as a chain of links which is modeled using a Markov chain and risk minimization. For the development of a translator we need some co-occurrence data across source and target spaces. Performance of the TLRisk framework was shown on text-aided image classification and on cross-language classification.

Software defect prediction is another important application area in transfer learning and software engineering. There is a possibility to build a prediction model with defect data collected from a software project and predict defects for new projects (cross-project defect prediction CPDP) (Nam et al., 2013; He et al., 2012; Ma et al., 2012; Rahman et al., 2012). However, projects must have the same metric set with identical meanings between projects. (Nam and Kim, 2015) introduce heterogeneous defect prediction (HDP) which allows heterogeneous metric sets across projects. At first they apply feature selection techniques to the source data. For feature selection they used various feature selection approaches widely used in defect prediction such as gain ratio, chi-square, relief-F, and significance attribute evaluation. Then the similarity between source and target data is computed and data is mapped. The similarity of each source and target metric pair is measured by using several existing methods such as percentiles, Kolmogorov-Smirnov test and Spearman's correlation coefficient. A model for target labels prediction is built using the mapped data.

3 FEATURE MAPPINGS

The main operation of transfer learning approaches is the mapping of features. These features originate from different feature spaces. We can map the features into common feature space or we can look for mapping from one feature space to another. Learning optimal mapping is a significant problem in the machine learning community. By mapping we mean a type of feature transformation which maps features from one feature space to another. We face many problems while mapping one feature space onto another: different number of features, dimensionality, distribution, used metrics etc. The number of possible mappings between source and target spaces grows exponentially as the number of features increases. The selection of a suitable mapping depends on the type of data – numerical (each data instance is a numerical feature vector) or structured (each instance is a structured object such as a string, a tree etc.), and on the specific problem. If the number of feature combinations doesn't pose a combinatorial problem, it is possible to realize feature mapping in a manual way. (van Kasteren et al., 2008) proposed a number of manual mapping strategies: intersect, duplicate, union. But manual mapping can be domain dependent as is shown in (van Kasteren et al., 2008). (van Kasteren et al., 2008) implemented their mapping solution for different sensors in house activity recognition.

State-of-art of feature mapping consists of preprocessing, dimensionality reduction and feature selection methods. There exist works, which concern themselves with dimensionality reduction (Si et al., 2010; Dai et al., 2009; Pan et al., 2008; Blitzer et al., 2006) and feature selection (Satpal and Sarawagi, 2007). We can also encounter feature weighting methods. But a wide spectrum of the methods covers the preprocessing phase. In this work several mapping approaches used within transfer learning are presented. We can divide them into statistic and metric methods. Statistic methods are represented primarily in the Spearman's correlation coefficient, Kolmogorov-Smirnov test, Kullback-Leibler divergence etc. We will focus more on pairwise metrics which are based on measuring the distance or similarity between data. As stated above, each problem pertains to a specific domain which has its own semantic notion of data similarity. This data similarity can be difficult to express through standard metrics such as Minkowski metrics (Bellet et al., 2013). The solution seems to be learning the metric from data. This approach is called metric learning or similarity learning(Bellet et al., 2013; Kulis et al., 2013; Yang, 2006).

3.1 Metrics

There exist a lot of metrics, which can be used (tested) during the mapping of features. The fundamental one is the family of Minkowski distances including Euclidean, Manhattan and Chebyshev distances. We can also use cosine similarity for measuring the cosine of the angle between two instances. It is widely used in data mining (e.g. bag-of-words or for sparse vectors). One of the popular methods for comparing structured data is standard (Levenshtein) edit distance and its mutations (e.g. Specific Cost Matrix, tree or stochastic edit distance), where we search for the smallest number of transformations (insertion, deletion or sub-

stitution of symbols), which is needed to transform one string to another (Bellet et al., 2013). Many metrics exist as well as some good surveys (Bellet et al., 2013; Kulis et al., 2013).

3.2 Metric and Similarity Learning

Similarity learning is a field of supervised learning and its task is to discover a similarity function from an example that measures similarity between two objects. It is closely related to metric distance learning, which finds a distance function between data. These two areas are closely connected to transfer learning or domain adaptation, where during the mapping of individual features between domains, we search for suitable methods of comparing the similarity of these features. We can then perform mapping based on these similarities which is represented by different transformations. We distinguish between linear (e.g. Mahalanobis distance learning and linear similarity learning) and nonlinear (e.g. kernelization of linear methods) metric learning (Wang et al., 2014; Saenko et al., 2010). The following survey on metric learning by (Bellet et al., 2013; Kulis et al., 2013; Yang, 2006) can serve for more details. Even though metric learning is a hot topic and is successfully used for problems in computer vision and other fields (e.g. (G. Chechik and Bengio., 2010; Kulis et al., 2009; Chopra et al., 2005)) as far as we know it is rarely used in the field of transfer learning and domain adaptation. We can find one of few applications in the symmetric approach by (Saenko et al., 2010) who present a method that adapts object models to new imaging conditions by supervised learning of transformations which minimizes the effect of domain-induced changes in the feature distribution.

This trend is similar to symmetric heterogeneous learning. However if a model is trained on one domain and then tested on another domain, it often results in poor performance (Saenko et al., 2010). One approach to this problem can be the generalization of the metric learning problem (Kulis et al., 2011). The idea is to learn a transformation A that maps the data from one domain to the other, thus leading to the inner product. This approach can be applied even when the dimensionalities of the two domains are different (Kulis et al., 2013).

(Chopra et al., 2005) propose a convolutional network for mapping data from source to target space. This method produces a non-linear mapping that can map any input vector of features to its corresponding version in lower dimension. It is also important that meta-features are learned from data and do not stem from prior knowledge about the task.

(Wang et al., 2014) propose a novel metric algorithm to transfer knowledge from source to target domain in metric settings called Cross-Domain Metric Learning (CDML). This method consists of three steps: 1) minimizing the distance between different distributions, 2) constructing two Gaussian distributions, one based on Mahalanobis distance to be learnt, second based on the information geometry (Wang and Jin, 2009) of target domain data, 3) constructing two more Gaussian distributions, one based on Mahalanobis distance again, the second one based on the labels and the geometry of source domain data. The results of these steps are combined into the unified loss function of CDML and by this combination the discriminating power gained from the labeled source domain data to the unlabeled target domain data is transferred.

Another usage of metric learning can be in unsupervised domain adaptation, where labeled source data and unlabeled target data for learning are available. The aim is to unify source and target distributions. The solution can be the usage of a nonparametric way of measuring the distribution difference between the source and target samples called Maximum Mean Discrepancy (MMD)(Bellet et al., 2013). This is used by (Geng et al., 2011) in a domain adaptation metric learning (DAML) algorithm. Further we encounter a transfer metric learning (TML) approach by (Zhang and Yeung, 2010), where the metric and the task covariances between the source and target tasks are learnt under a unified convex formulation. Their work is based on multi-task metric learning with transfer learning settings.

4 CONCLUSION AND CHALLENGES

The majority of heterogeneous transfer learning approaches transfer source and target features to common feature space (see Section 2.1). The minority of works concern themselves with the direct mapping of source features to target features (see Section 2.3), which is significantly more demanding because of the necessity to search for a suitable mapping between disparate but related spaces. The solutions are limited if we are dealing with labeled or unlabeled data. Also a lot of work is done in computer vision and in text classification, but there are a lot of other domains, e.g. medical data or student performance data, where transfer learning could be applied. There are a lot of manual mapping strategies, but the problem remains in their automatization together with finding the optimal mapping. Optimal mapping means that the map-

ping is feasible in both directions between source and target feature spaces. A lot of data is task or domain specific and so the generalization of mapping transformations poses a challenge. There are two ways of automatic feature mapping: trying multiple mappings or mapping by analogy. This is often computationally very demanding. There are also some complications with the lack of overlap between feature spaces and different dimensionality. We also have to consider, whether there is any correspondence between features. One of the remaining questions is the negative transfer within asymmetric heterogeneous transfer learning and varying data. Also the adaptation of metrics to varying data (e.g. lifelong learning, detection of concept drifts).

The main contribution of this paper is to provide a summary of available up-to-date approaches and methods in the area of heterogeneous transfer learning. We also aim to emphasize some of the open challenges within this area. Our future work will consist of finding suitable feature mappings between different source and target spaces. We would like to use these mapped features, more precisely the data, in machine learning models which were learnt on data not mapped and evaluate their relative performance. This paper forms a base for future work in the field of asymmetric heterogeneous transfer learning using methods of metric learning – this combination is not very common as far as we know and thus it is one of the main challenges which could bring an automatized and generalized solution for asymmetric heterogeneous transfer learning problems.

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