An Overview of Transfer Learning and Computational CyberPsychology

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Abstract. Computational CyberPsychology deals with web users' behaviors, and identifying their psychology characteristics using machine learning. Transfer learning intends to solve learning problems in target domain with different but related data distributions or features compared to the source domain, and usually the source domain has plenty of labeled data and the target domain doesn't. In Computational CyberPsychology, psychological characteristics of web users can't be labeled easily and cheaply, so we "borrow" labeled results of related domains by transfer learning to help us improve prediction accuracy. In this paper, we propose transfer learning for Computational CyberPsychology. We introduce Computational CyberPsychology at first, and then transfer learning, including sample selection bias and domain adaptation. We finally give a transfer learning framework for Computational CyberPsychology, and describe how it can be implemented.

Keywords: Computational CyberPsychology, transfer learning, machine learning

1 Introduction

The internet develops rapidly and plays an important role in people's life, thus it becomes important to understand how people behave on the web. CyberPsychology focuses on the association between virtual behaviors and psychological characteristics on internet. However, most research use questionnaires to assess individual psychological traits, which is a bit time-consuming and expensive. To cope with this problem, we propose to use machine learning and other techniques to build computational models of web behavior and psychological characteristics [1], i.e., Computational CyberPsychology(CCP).

In traditional machine learning, instances in training and testing dataset are presumed to follow independent identical distribution(IID). However in CCP, it is quite often that training data(source domain) and testing data(target domain) follow different distributions, thus cannot meet the IID assumption. For this reason, traditional machine learning techniques perform poorly. Transfer learning is designed to transform data and knowledge from source domain to target domain

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to make better predictions on target domain, which motivates us to explore the possibility to adapt it on CCP.

The rest of paper is organized as follows: in Section 2, we introduce CCP and the necessity using transfer learning on CCP. We then describe transfer learning briefly in Section 3. In Section 4, we present a transfer learning framework for CCP. Finally, we conclude the paper and refer to our future work in Section 5.

2 Computational CyberPsychology

For years, psychologists have been studying the association between web behavior and psychological characteristics by questionnaires [2]. However, the self-report method can be negatively influenced by participants' subjective involvement [3]. Technically, we can obtain a large quantity of web behavior data [3], and use machine learning to build computational model for predicting users' psychological characteristics [1]. The recent research results is inspiring [1], [4].

Following a general CCP procedure, we collect web user's behaviors on the internet, preprocess and extract behavioral features, and build users' computational psychology models, which then can be used to predict psychological characteristics. Psychological characteristics include personality, mental health status, society well-being, etc. The web behavior has various types of web data, including interaction on SNS and microblogs, searching, communicating with Emails, chatting with IM, playing games and users' behaviors recoded as logs on gateway servers or browsers, and etc [3].

To build a model for identifying association between users' web behaviors and the psychological characteristics, supervised learning methods would be used as the first choice. However, if the training and test data are drawn from different feature space or different distributions, the supervised learning methods usually do not work well. In such cases, we can use information of related domains and bring in transfer learning to train a better classifier. For example, if we want to predict graduate students' personality based on their web behaviors, but unfortunately few labeled samples available. So the traditional classification methods perform poorly. Meanwhile, we have plenty of labeled data of undergraduate students. Graduate students and undergraduate students have similar on-line time, related working behaviors, and other similar web behaviors. Thus, it would be helpful for training a better classifier on graduate students that we transfer the undergraduate students' classification knowledge to the graduate students domain through transfer learning.

3 Transfer learning

In recent years, transfer learning becomes an important research area in machine learning, which is originally introduced in NIPS95 workshop [5]. Since there is much difference in data distributions and data features between training and testing data set, traditional supervised or semi-supervised methods perform poorly. We can make use of these different but related dataset in a transfer learning way to improve the performance of classifiers for target task. Transfer learning was defined by Pan et al. [5] as:

Definition: *Given a source domain D_S and learning task T_S, a target domain D_T and learning task T_T, transfer learning aims to help improve the learning of the target predictive function f_T in D_T using the knowledge in D_S and T_S, where $D_S \neq D_T$ or $T_S \neq T_T$.*

In the above definition, the data difference between source domain and target domain usually includes, the difference of data distributions, the difference of data features, and the difference of label criteria. In CCP, we focus on problems that source domain differs from target domain, but following the same label criteria. They consist of two types of problems: one is distribution transfer, to solve problems with different distributions between source and target domain, i.e., sample selection bias or data shifting; the other is feature transfer, for different features between source domain and target domain, i.e., domain adaptation.

3.1 Sample Selection Bias

Most distribution transfer approaches are motivated by importance sampling [5]. The distribution transfer solution is to learn the optimal value of unknown parameter by minimizing the expected risk on all instances of target domain. A common representation is as follows [5]:

$$\theta^* = \arg\min_{\theta \in \Theta} \mathbb{E}_{(x,y)\in P}[l(x,y,\theta)].$$

where x is the input sample data, y is the corresponding label, P is the labeled data set, θ is the optimal model parameters that will be determined, and $l(x,y,\theta)$ is the risk. In reality, we finally calculate $P(x_{S_i})/P(x_{T_i})$ as follows [5]:

$$\theta^* \approx \arg\min_{\theta \in \Theta} \sum_{i=1}^{n_S} \frac{P(x_{S_i})}{P(x_{T_i})}[l(x_{S_i}, y_{S_i}, \theta)].$$

where $P(x_{S_i})$ is probability of a instance in source domain, while $P(x_{T_i})$ is probability of a instance in target domain.

To estimate the ratio, Huang et al. [6] proposed a kernel-mean matching (KMM) algorithm, which directly produces resampling weights by distribution matching between training and testing sets in feature space. Sugiyama et al. [7] further proposed an algorithm Kullback-Leibler Importance Estimation Procedure (KLIEP) to estimate $P(x_{S_i})/P(x_{T_i})$ directly, which behaved well due to add an automatic model selection procedure. In CCP, we can directly apply the above framework for distribution transfer problems.

For more related recent research about data set shift, Storkey[8] represented a number of data shift models, including covariant shift, prior probability shift, sample selection bias, shift on imbalanced data, domain shift and etc. Bickel et al. [9] proposed a integrated optimization method for discriminative learning problem under covariant shift.

3.2 Domain Adaptation

To cope with domain adaptation, Blitzer et al. [10] proposed a method in Structural Correspondence Learning(SCL) framework. The method begins with extracting some relevant features(called pivot features) to bridge source and target domain. Then it constructs some auxiliary classification tasks, and obtains a projection from the original feature space to shared feature representation. Finally, it trains a classifier on augmented feature space combining the shared features and the original features. Daume III et al. [11] proposed a very easy algorithm, which put source domain feature, target domain feature and shared features into one structure, and then used a standard discriminative method to train classifiers. Chang et al. [12] argued that adaptation combining both unlabeled adaptation frameworks and labeled adaptation frameworks would perform better. These methods depend on extracting explicated or implicated common features of the two domains, but their disadvantages lie that, these common features usually can't be obtained in a simple way. So the algorithms can only be adapted to limited situations. All above algorithms were developed for NLP problems. When we deal with CCP problems, to find pivot features of SCL framework would be domain dependent, and Daume III's algorithm remind us to construct an augmented feature representation.

For another type of transfer learning called heterogeneous transfer learning where features of both domains have totally different feature spaces, there have been no general solution. However, these heterogeneous transfer learning methods may provide ideas and choices to solve some CCP problems. Yang et al. [13] proposed an algorithm, which improved unsupervised learning by transferring knowledge from auxiliary heterogeneous data and using an extended PLSA method. Zhu et al. [14] proposed a heterogeneous transfer learning framework for knowledge transfer between text and images. They used collective matrix factorization (CMF) to learn a common latent semantic space for image and text data, and trained a classifier in the new space. Argyriou et al. [15] considered a heterogeneous environment in which tasks could be divided into groups, and proposed an algorithm which could group tasks and computed a common representation for all groups in a low dimensional feature space.

4 Transfer Learning Framework for Computational CyberPsychology

Here, we propose a framework for transfer learning in CCP. Firstly, we measure web users in source domain and label their psychological characteristics such as personality through psychology assessment. Then, we collect web log and other information of these labeled users and other few-labeled users from a different domain(target domain), and preprocess the data according to researcher-defined web features. After that, transfer learning is used to learn association between data of both domains, and train a better classifier to predict what unlabeled users' psychological characteristics are.

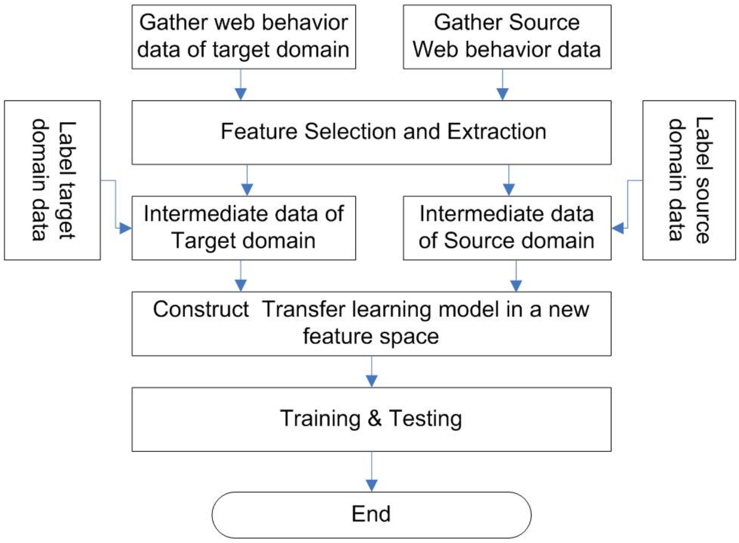

Fig. 1. A procedure of a transfer learning framework

We show a general framework to do transfer learning for CCP in Fig. 1, in which various transfer methods can be analyzed and compared more conveniently and more completely. The framework is as follows:

$$\min_{w_t, w_s, \Phi} R(x_t, y_t, w_t) + \mu R(\Phi(x_s, y_s, w_s, x_t, y_t, w_t)) + \lambda \|(w_t, w_s, \Phi)\|_f.$$

Where x_t, y_t and w_t, is the sample, the responding label, and the parameter that will be learned in target domain, x_s, y_s and w_s is x_t, y_t and w_t's correspondence in source domain, μ and λ are ratio-constant terms, Φ is a transfer function or transfer operator, and $\|(w_t, w_s, \Phi)\|_f$ is a f-norm of combining w_t, w_s, Φ. There are three parts separated by sign "plus". The first part represents a risk function over inadequate labeled samples in the target domain, which can be acquired by supervised learning. The second part is transfer risk, and it represents distribution-transfer risk and feature-transfer risk. The third part controls the complexity of transfer and training function, and it is often regarded as a regular term. In some particular situation, the equation should be adapted or just simplified.

We can utilize transformations of those methods described in Section 3 to apply this transfer learning framework. As the graduate example in Section 2, if graduate students and undergraduate students have identical features, but different distributions, we would choose distribution transfer methods to solve the problem. In fact, we should firstly test whether distributions of both domains are identical by T-test or other method. If they are identical, then supervised learning can meet the requirement. Otherwise, we can try using Sugiyama's method or other method to represent transfer risk for this problem. We usually face the situation that users in target domain are labeled only a few, and these users data can put into the first part to work. As to the third part, it indicates a prior of the optimal model parameters, or can be omitted.

Another example, suppose we collect users' web-behavior data and extract feature information from social network sites (SNS) and gateway independently, and use these data to predict users' personality. Gateway has much less samples than SNS and is taken as the target domain, while SNS is the source domain. In this case, the features from each domain have different categories. Facing this problem, we can introduce extend PLSA method to transfer data from the original features space to a common latent variable representation, and then train a model over both domains under the transfer risk. In addition, we represent the transfer (function) complexity and training function complexity over latent variable representation in the third part. Much more, if there are some features in both domains having equivalent semantics, we can apply Daume III's method in some way.

5 Conclusion

CCP concerns about users' psychology characteristics through their web behaviors. Due to the complexity of web psychological phenomenon, it brings many challenges to machine learning especially transfer learning. We discussed the necessity of transfer learning for CCP, gave an overview about CCP, briefly surveyed sample selection bias issue and domain adaptation issue in transfer learning, and finally gave a transfer learning framework for CCP. In the future, we will construct a more specific transfer learning framework for CCP, and develop new transfer learning algorithms corresponding psychological analysis methods.

6 Acknowledgment

The authors gratefully acknowledges the generous support from NSFC(61070115), Research-Education Joint Project(110700EA02) and 100-Talent Project(110700M202) from Chinese Academy of Sciences.

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