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Fast and Scalable Semi Supervised Adaptation for Video Action Recognition

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Abstract:

A new and efficient semi supervised adaptation method is used for parameter estimation and feature selection in Conditional Random Fields (CRFs). In real world applications such as activity recognition, unlabeled sensor traces are relatively easy to obtain whereas labeled examples are expensive and exhausting to collect.Automatically choose atiny low set of discriminatory options from anoutsized pool is advantageous in terms of process speed still as accuracy.In this paper, the semi supervised virtual evidence boosting algorithmic program is introduced for CRFs and a semi supervised extension to the recently developed virtual evidence boosting method for featureselection and parameter learning Semi-supervised Domain Adaptation with Subspace Learning (SDASL), which jointly explores invariant low- dimensional structures across domains to correct data distribution mismatch and leverages available unlabeled targetexamples to use the underlying intrinsic data within the target domain.

Keywords **—Adaptation, Human action recognition, Semi-supervised learning.**

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I. INTRODUCTION

Conditional random fields (CRFs) are undirected graphical models that have been successfully applied to the classification of relational and temporal data. The complex CRF models with a huge amount of input features is slow, and exact its inference often intractable. The ability to select the most informative features as needed can reduce the training time and the risk of over-fitting of parameters. Furthermore, in complex modeling tasks, obtaining the large amount of labeled data necessary for training can be impractical. On the other hand, large unlabeled datasets are often easy to obtain, making semi-supervised learning methods appealing in various real-world applications. The goal of our work is to build an activity recognition system that is not only accurate but also scalable, efficient, and easy to train and deploy. An important application domain for activity recognition technologies is in health-care, especially in supporting elder care, managing cognitive disabilities, and monitoring long-term health.

Activity recognition systems will also be useful in smart environments, surveillance, emergency and military missions. Some of the key challenges faced by current activity inference systems are the amount of human effort spent in labeling and feature engineering and the computational complexity and cost associated with training. Data labeling also has privacy implications because it often requires human observers or recording of video.

In this paper, introduce a fast and scalable semi-supervised training algorithm for CRFs and evaluate its classification performance on extensive real world activity traces gathered using wearable

sensors. In addition to being computationally efficient, proposed method reduces the amount of labeling required during training, which makes it appealing for use in real world applications.

The objective function in VEB is a soft version of maximum pseudo-likelihood (MPL), where the goal is to maximize the sum of local log-likelihoods given soft evidence from its neighbors. This objective function is similar to that used in boosting, which makes it suitable for unified feature selection and parameter estimation. This approximation applies to any CRF structures and leads to a significant reduction in training complexity and time. Semi-supervised training techniques have been extensively explored in the case of generative models and naturally fit under the expectation maximization framework. However, it is not straight forward to incorporate unlabeled data in discriminative models using the traditional conditional likelihood criteria.

CRFs are proposed for a few semi-supervised training methods that introduce the dependencies between nearby data points. More recently, proposed a minimum entropy regularization framework for incorporating unlabeled data.

In this project, combine the minimum entropy regularization framework for incorporating unlabeled data with VEB for training CRFs. The contributions of this project are:

(i) Semi-supervised virtual evidence boosting (sVEB) - an efficient technique for simultaneous feature selection and semi-supervised training of CRFs, which to the best of our knowledge is the first method of its kind.

(ii) Experimental results that demonstrate the strength of sVEB, which consistently outperforms other training techniques on synthetic data and real-world activity classification tasks, and

(iii) Analysis of the time and complexity requirements of our algorithm, and comparison with other existing techniques that highlight the significant computational advantages of our approach.

A fast and easy to implement the sVEB algorithm and has the potential of being broadly applicable.

II. LITERATURE SURVEY

Refer to the problem as supervised domain adaptation. Adaptive support vector machine (ASVM) is proposed to learn a new SVM classifier for the target domain, which is adapted from an existing classifier trained with the samples from a source domain. A new dimensionality reduction method called maximum mean discrepancy embedding (MMDE) for domain adaptation, which aims to learn a shared latent space where distance between distributions can be reduced while the data variance can be preserved.

A parameterized augmented space as the common space motivated by a domain adaptation method and the parameters were learnt through optimizing a large margin classification model. The earliest papers to research domain adaptation in visual recognition by metric learning techniques that aim to be told a change learn a transformation that minimizes the impact of domain induced changes.

Semi-supervised domain adaptation methods to not only include subspace representations of the two languages of both labeled and unlabeled documents. Besides of the use of unlabeled target examples as in these aforementioned semi supervised methods, additionally incorporates the objective of obtaining a subspace on which data distribution mismatch is reduced and original structure properties are preserved.

III. PROPOSED SYSTEM

The main goal of semi-supervised domain adaptation with subspace learning (SDASL) is to bridge subspace representations of the two languages of both labeled and unlabeled documents. Besides of the use of unlabeled target examples as in these aforementioned semi supervised methods, approach additionally incorporates the objective of obtaining a subspace on which data distribution

mismatch is reduced and original structure properties are preserved.

The training of SDASL is performed simultaneously by minimizing the classification error, preserving the structure relationships within and across domains, and restricting similarity defined on unlabeled target instances. In particular, the objective function of SDASL is composed of three components, i.e., structural risk, structure preservation within and across domains, and manifold regularization. After we have a tendency to get predictive function on the subspace, the label of a new coming target instance can be determined accordingly. In the following, first introduce the annotations used in this paper, followed by constructing the three learning components of SDASL. Then the joint overall objective and its improvement strategy are provided. Finally, the whole SDASL algorithm for visual recognition is presented. Proposed system focus on the scenario when transferring only from one source.

However, the proposed methodology is extended to multiple sources. Suppose plenty of labeled source data and only a limited number of labeled target data. Additionally we are given unlabeled target data. Goal is to help tasks in a label-scarce target domain by transferring the information in the label-rich source domain.

IV. CONCLUSION

In this paper, presented semi-supervised domain adaptation with subspace learning for visual recognition. Particularly, explore a new feature representation in the subspace which could reduce the data distribution mismatch across domains and preserve structure properties of the original data. Meanwhile, because the unlabeled target examples exhibit the underlying intrinsic data within the target domain, these examples are further more utilized to generalize the visual concept classifier. Experiments conducted on both image-to-image and image-to-video transfers validate the proposal and analysis.

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