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A visual analytical approach for transfer learning in classification

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ABSTRACT

Classification can be highly challenging when the dataset is extremely large, or when the training data in the underlying domain are difficult to obtain. One feasible solution to this challenge is transfer learning, which extracts the knowledge from source tasks and applies the knowledge to target tasks. Extant transfer learning schemes typically assume that similarities between the source task and the target task to some degree. This assumption does not hold in certain actual applications; analysts unfamiliar with the learning strategy can be frustrated by the complicated transfer relations and the non-intuitive transfer process. This paper presents a suite of visual communication and interaction techniques to support the transfer learning process. Furthermore, a pioneering visual-assisted transfer learning methodology is proposed in the context of classification. Our solution includes a visual communication interface that allows for comprehensive exploration of the entire knowledge transfer process and the relevance among tasks. With these techniques and the methodology, the analysts can intuitively choose relevant tasks and data, as well as iteratively incorporate their experience and expertise into the analysis process. We demonstrate the validity and efficiency of our visual design and the analysis approach with examples of text classification.

1. Introduction

Conventional data analysis approaches assume that the training and test data are drawn from the same feature space and the same distribution. Knowledge transfer, also known as transfer learning, seeks to fulfill a new task by leveraging the knowledge and insights from accomplished tasks. The mechanism of transfer learning is similar to the "learning by analogy" approach, which understands a new situation by leveraging familiar conditions [21]. The "*source analog*" is an existing situation that conveys information and reference in exploring a novel "target", with its main concern found in the similarity between the source and the target. The concept of "learning by analogy" that comes from cognitive psychology is relatively abstract, whereas transfer learning algorithms provide a formal description of analogy between learned tasks and new tasks in machine learning. The new task can be in the same scenario with the source tasks or even a different scenario, given that a type of analogy exists between the tasks or the underlying datasets. As such, transfer learning can be used to

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analyze a large amount of data by first training a part of it and transferring the result to the remaining data [40]. Similarly, knowledge transfer can be performed between two tasks performed in two different applications.

Transfer learning is truly beneficial because it can significantly reduce the cost and burden of exploring unknown data and unknown scenarios, and help discover common features hidden in tasks and data from different application fields. One example is the classification of web documents, in which bundles of data from different sources (e.g., forums, news press, and websites) are handled. Each data source has a specific word distribution, and leads to a unique data classification model. For a new data source, directly applying existing classification models will cause a performance drop. Transfer learning has proven to be significantly useful [14].

Despite the progress of transfer learning, many challenges exist regarding its usage in real applications. The most important challenge is the estimation of the *transferability* between the task pairs or the data pairs. The transferability actually measures the capability of the knowledge transfer for a specific task. With an appropriate transferability, the analyst can easily choose existing analysis results analogous to the target task, and perform the transfer. Conversely, determining the *reusability* of data instances for the new task is non-trivial. Both challenges cannot be fully addressed with an automatic transfer learning process when handling a complicated scenario, and may be aggravated by the complicated transfer relations and the non-intuitive transfer process.

We argue that applying visualization techniques in the learning process would be an effective means for incorporating the human intelligence into complicated analysis tasks. In particular, visualization technologies that integrate the intelligences from both the machine and human within a visual information communication interface have achieved significant success on many areas, including classification [17,23], summarization, and clustering [11,25,49]. These techniques could be certainly adapted to the transfer learning process to bridge the gap between the domain experts and the transfer learning approaches.

This paper presents a pioneering visual-assisted transfer learning scheme in the context of text classification. The core idea of our work lies in our design of a suite of visualization communication and interaction techniques to enhance the analyst's understanding and the manipulability of the knowledge transfer process. By incorporating the domain experiences and expertise into the knowledge transfer process within a visual exploration loop, the analyst can intuitively study the relevances among various tasks and data, and identify similar tasks. For analogous tasks, the analyst can interactively choose the related data instances, and use the trained data for a new task, which is supported by a pioneering visual representation of the classification result and the data instance similarity. To our best knowledge, our work is the first effort to apply visualization methods to the knowledge transfer process, and leads to the following main contributions:

- a suite of visual communication and interaction techniques that support the knowledge transfer process;
- a pioneering visual analytics based transfer learning methodology capable of analyzing relevances between different tasks and knowledge transfer on the level of data instances;
- an exploratory data classification prototype called TransXplorer that follows the proposed techniques and methodology, and demonstrates high efficiency for text classification.

The rest of the paper is organized as follows. Section 2 summarizes related works. Section 3 provides the overview of the entire transfer learning framework. Sections 4 and 5 present detailed descriptions of its two stages. Section 6 presents experimental results and analysis. Section 7 present discussion and Section 8 draws conclusions.

2. Related work

A large body of literature is devoted to machine learning and text classification. Below, we briefly review the most relevant ones.

Text classification: Text classification deals with text feature representation and classification rules. First, feature representation plays an important role in text classification. Each text classification task requires specific text feature measurements. Successful text classification methods should choose the classification criteria relatively suitable for the text classification object and text data types. Common text features include Mutual Information, Latent Semantic Indexing [41], Linear Discriminant Analysis [33], and so on. Suitable feature selection is the key of the text classification process. Then, valuable feature representation selection rules from source tasks should be regarded as knowledge transferred to target tasks.

Second, as to classification rules, different text data require specific classification methods to effectively account for text features. Some common classification methods include decision trees [22], pattern-based classifiers [22], SVM classifiers [47], Neural Network classifiers [22], Bayesian Classifiers [22], and so on. Each classifier is designed to satisfy a concrete text classification. For example, decision trees aimed at hierarchical division of the underlying data space using different text features; SVM classification is suitable for high-dimensional sparse features; Naive Bayesian is used for some simple application environments.

Different tasks require different text classification methods, which indicate that human knowledge could play an important role in text classification because humans can use their experience and expertise to decide suitable text classification features and classification rules.