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Summary of Deep Transfer Learning

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Abstract

As a new classification model, deep learning has been paid more and more attention by researchers in recent years and has been successfully applied in many fields. In the fields of bioinformatics and robotics, it is very difficult to construct large-scale well-annotated data sets because of the high cost of data collection and annotation, which limits the development of data sets. Migration learning doesn't require that the training data must be independent and distributed with the test data, which inspires us to use migration learning to solve the problem of insufficient training data. This paper summarizes the research status and application of deep neural network in transfer learning. We define deep transfer learning and its classification, and review the research work based on deep transfer learning technology in recent years.

Keywords

Deep Learning; Transfer Learning; Neural Network.

1. Introduction

In recent years, deep learning has been paid more and more attention by researchers, and has been successfully applied in many practical applications. Deep learning algorithm tries to learn advanced features from massive data, which makes deep learning surpass traditional machine learning. It can automatically extract data features through unsupervised or semi-supervised feature learning algorithms and hierarchical feature extraction. In contrast, traditional machine learning methods require manual design, which seriously increases the burden on users. It can be said that deep learning is a representation learning algorithm based on large-scale data in machine learning [1].

Data dependence is one of the most serious problems in deep learning. Compared with traditional machine learning methods, deep learning relies heavily on massive training data, because it requires a large amount of data to understand the potential patterns of data. An interesting phenomenon is that the size of the model is almost linear with the amount of data needed. A reasonable explanation is that for a specific problem, the expression space of the model must be large enough to discover the patterns under the data [2-4]. The predetermined layer in the model can identify the high-level characteristics of the training data, and the subsequent layer can identify the information needed to help make the final decision.

Insufficient training data is an inevitable problem in some special fields. Data collection is complicated and expensive, which makes it very difficult to build large-scale and high-quality annotated data sets. For example, every sample in bioinformatics data set often shows a clinical trial or a painful patient. In addition, even if we pay a high price to obtain the training data set, it is easily outdated and cannot be effectively applied to new tasks.

Transfer learning relaxes the assumption that training data must be independent and distributed (i.i.d) with test data, and encourages us to use transfer learning to solve the problem of insufficient training data [5]. In transfer learning, training data and test data need not be i.i.d There is no need to train the

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model in the target domain from scratch, which can significantly reduce the demand for training data and training time in the target domain.

In the past, most of the researches on transfer learning used traditional machine learning methods. Because of the dominant position of deep learning in modern machine learning methods, the research on deep transfer learning and its application is particularly important. The contributions of this review are as follows:

-We defined deep transfer learning for the first time and divided it into four categories.

-We reviewed the current research work on various categories of deep transfer learning, and gave the standardized description and schematic diagram of each category.

2. Deep transfer learning

Transfer learning is an important tool to solve the basic problem of insufficient training data in machine learning. It tries to transfer knowledge from the source domain to the target domain by relaxing the assumption that training data and test data must be i.i.d This will have a great positive impact on many fields that are difficult to improve due to insufficient training data. The learning process of transfer learning is shown in Figure 1 [6].

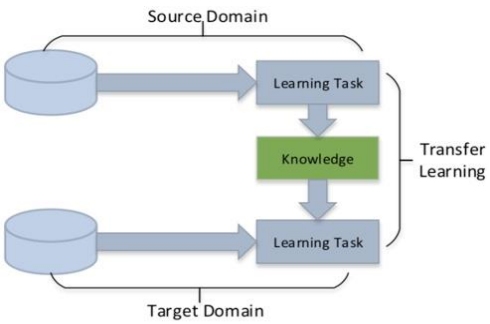

Fig. 1 Transfer learning process

Some symbols used in this article need to be clearly defined. First of all, we give a definition of a domain and a task: a domain can be expressed as D ={χ, P (X)}, which consists of two parts: feature space χ and marginal probability distribution P (X), X = {x1, …, xn} ∈χ. A task can be expressed by T = {y, f(x)}. It consists of two parts: label space y and target prediction function f(x). F(x) can also be regarded as a conditional probability function P(y|x). Then, transfer learning can be formally defined as:

Definition 1. (Transfer Learning) Given a Dt-based learning task Tt, you can get help from the Ds of the learning task Ts. Migration learning aims to improve the performance of prediction function ft () by discovering and migrating the potential migratable knowledge of Ds and Ts for learning task Tt, where Ds is not equal to Dt and/or T is not equal to Tt. In addition, in most cases, the size of Ds is much larger than that of Dt, Ns≫Nt.

In recent years, deep learning has gained a dominant position in many research fields. How to use deep neural network to transfer knowledge effectively is very important. This is called deep transfer learning, which is defined as follows:

Definition 2. (Deep Migration Learning) Give a learning task migration definition DS, Ts, Dt, Tt, FT (…). This is a deep transfer learning task, in which ft () is a nonlinear function reflecting the deep neural network.

3. Classification of deep transfer learning

Deep transfer learning is to study how to use knowledge from other fields through deep neural networks [7]. With the wide application of deep neural networks in various fields, a large number of

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deep transfer learning methods have been proposed, and it is very important to classify and summarize them. Based on the technology of deep migration learning, this paper divides deep migration learning into four categories: case-based deep migration learning, mapping-based deep migration learning, network-based deep migration learning and confrontation-based deep migration learning, as shown in Table 1.

Table 1. Deep transfer learning classification

Approach category	Brief description	Some related works
Instances-based	Utilize instances in source domain by appropriate weight.	[4],[27],[20],[24],[10],[26],[11]
Mapping-based	Mapping instances from two domain into a new data space with better similarity.	[23],[12],[8],[14],[2]
Network-based	Reuse the of network pre-trained in the source domain.	[9],[17],[15],[30],[3],[6],[28]
Adversarial-based	Use adversarial technology to find transferable features that both suitable for two domains.	[1],[5],[21],[22],[13],[16]

3.1 Case-based Deep Migration Learning

Case-based deep migration learning refers to adopting a specific weight adjustment strategy, selecting some instances from the source domain as a supplement to the training set of the target domain, and assigning appropriate weights to these selected instances. It is based on the assumption that "although there are differences between the two domains, some instances in the source domain can be utilized by the target domain with appropriate weights."

TrAdaBoost uses plug-in technology to filter out situations different from the target domain in the source domain. Re-weight instances in the source domain to form a distribution similar to the target domain. Finally, the model is trained by using re-weighted instances from the source domain and from the target domain. On the premise of guaranteeing the performance of the algorithm, the algorithm reduces the weighted training errors in different distribution domains [8]. TaskTrAdaBoost is a fast algorithm, which can promote the rapid retraining of new targets. Different from TrAdaBoost's design for classification problem, R2 proposes that in order to solve the regression problem, the dual weight domain adaptive algorithm (BIW) can align the feature spaces of two domains into a common coordinate system, and then assign appropriate weights to the instances in the source domain.

3.2 Deep Transfer Learning Based on Mapping

Mapping-based deep migration learning refers to mapping instances from source domain and target domain to new data space. In this new data space, the examples from the two domains are similar, which is suitable for joint deep neural networks. It is based on the assumption that "although there are differences between two source domains, they may be more similar in a complex new data space." The schematic diagram of case-based deep migration learning is shown in Figure 2.

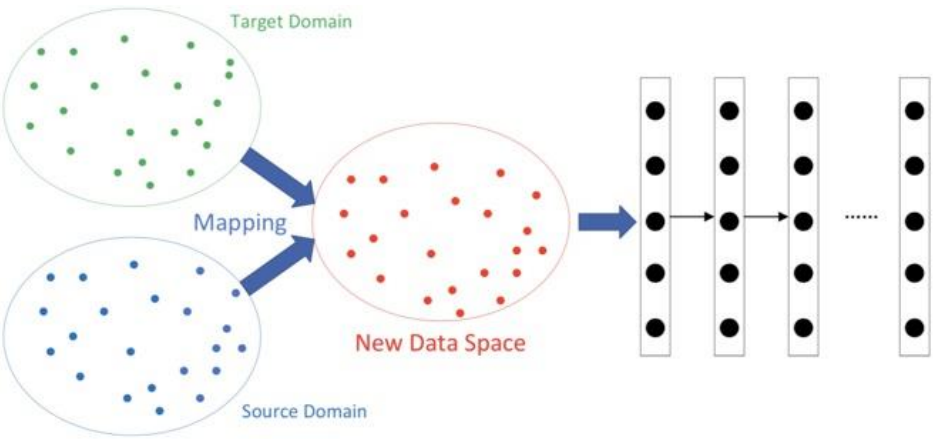

Fig. 2 Schematic diagram of deep migration learning based on mapping

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Meanwhile, the instances from the source domain and the target domain are mapped to a new data space. All instances in the new data space are regarded as training sets of neural networks.

Transfer Component Analysis (TCA) has been widely used in many applications of traditional transfer learning. It is a natural idea to extend TCA method to deep neural network. MMD is extended to compare the distribution in deep neural networks, and a semantically meaningful and domain-invariant representation is learned by introducing an adaptive layer and an additional domain confusion loss. The MMD distance used in this work is defined as

$$D_{MMD}(X_S, X_T) = \left\| \frac{1}{|X_S|} \sum_{x_s \in X_S} \phi(x_s) - \frac{1}{|X_T|} \sum_{x_t \in X_T} \phi(x_t) \right\| \tag{1}$$

$$L = L_C(X_L, y) + \lambda D_{MMD}^2(X_S, X_T) \tag{2}$$

Use multi-core MMD distance instead of MMD distance. In this paper, hidden layers related to learning tasks in Convolutional Neural Network (CNN) are mapped to reconstructed kernel Hilbert space (RKHS), and the distance between different domains is minimized by multi-core optimization method. Joint Maximum Mean Deviation (JMMD) is used to measure the relationship of joint distribution. The transmission learning ability of deep neural network (DNN) is extended by JMMD method to adapt to the data distribution in different fields, and the existing work is improved. Wasserstein distance can also be used as a new domain distance measurement method to find a better mapping.

3.3 Deep Migration Learning Based on Network

Network-based deep migration learning refers to reusing some pre-trained networks in the original domain, including their network structure and connection parameters, and transforming them into a part of the deep neural network used in the target domain. It is based on the assumption that neural network is similar to the processing mechanism of human brain and is an iterative and continuous abstract process. The front layer of the network can be regarded as a feature extractor, and the extracted features are universal.

Firstly, the network is trained in source domain by using large-scale training data sets. Secondly, part of the network that preprocesses the source domain is migrated to the new network designed for the target domain. Finally, the fine tuning strategy can be updated for the transmitted sub-network.

The network is divided into two parts, the first part is language-independent feature transformation, and the last layer is language-related classifier. Language-independent feature transformation can be transformed between multiple languages. Reuse the front layer of CNN training on ImageNet dataset to calculate the intermediate image representation of images in other datasets [9]. CNN is trained to learn image representation, which can be effectively migrated to other visual recognition tasks with limited training data.

The adaptive classifiers and migratable features of labeled data in the source domain and unlabeled data in the target domain are jointly studied. By inserting multiple layers into the deep network, the residual function is explicitly learned by referring to the target classifier. Learning domain adaptation and deep hash feature exist in DNN simultaneously. A new multiscale convolutional sparse coding method. This method can automatically learn filter banks at different scales, and combined with the forced scale specificity of the learning mode, it provides an unsupervised solution for learning the basic knowledge that can be migrated and fine-tuning the target tasks. The knowledge of applying deep migration learning to real object recognition task is transformed into the fault classifier of multi-gravitational wave signal detector. The results show that DNN can be used as an excellent feature extractor in unsupervised clustering method, and can identify new classes according to morphological features without using any labeled instances.

Another very noteworthy thing is the relationship between network structure and portability. The results show that some modules may not affect the accuracy in the domain, but will affect the portability. It points out which features are migratable in the deep network and which types of

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networks are more suitable for migration. It concludes that LeNet, AlexNet, VGG, Inception and ResNet are better choices for deep migration learning based on network.

3.4 Deep Migration Learning Based on Confrontation

Deep transfer learning based on antagonism refers to the introduction of antagonism technology inspired by the generation of antagonism network (GAN), which is suitable for both source domain and target domain. It is based on the assumption that "in order to transfer effectively, a good representation should be the distinction between the main learning tasks and the indistinguishability between the source domain and the target domain."

In the training process of large-scale data sets in the source domain, the front layer of the network is used as the feature extractor. It extracts features from two domains and sends them to the confrontation layer. The confrontation layer tries to distinguish the source of features. If the performance of the countermeasure network is poor, it means that the difference between these two types of features is small and the mobility is good, and vice versa. In the following training process, the performance of the antagonism layer will be considered, forcing the migration network to find more general characteristics with portability.

4. Conclusion

In this review, the current research on deep transfer learning is reviewed and classified. Deep migration learning is divided into four categories for the first time: case-based deep migration learning, mapping-based deep migration learning, network-based deep migration learning and confrontation-based deep migration learning. In most practical applications, in order to get better results, these technologies are often used in combination. At present, most of the researches focus on supervised learning, and how to use deep neural network to transfer knowledge in unsupervised or semi-supervised learning may attract more and more attention in the future. Negative transfer and transferability measurement are important issues in traditional transfer learning. The influence of these two problems on deep transfer learning needs further study. In addition, a very attractive research field is to find stronger physical support to transfer knowledge in deep neural networks, which requires the cooperation of physicists, neuroscientists and computer scientists. It can be predicted that with the development of deep neural network, deep transfer learning will be widely used to solve many challenging problems.

References

[1] Markus Johannes Ankenbrand, David Lohr, Wiebke Schlötelburg, Theresa Reiter, Tobias Wech, Laura Maria Schreiber. Deep learning-based cardiac cine segmentation: Transfer learning application to 7T ultrahigh-field MRI[J]. Magnetic Resonance in Medicine, 2021, 86(4).

[2] Xia Min, Shao Haidong, Williams Darren, Lu Siliang, Shu Lei,de Silva Clarence W.. Intelligent Fault Diagnosis of Machinery Using Digital Twin-assisted Deep Transfer Learning[J]. Reliability Engineering & System Safety, 2021(prepublish).

[3] Mishra Shreyas. Deep Transfer Learning-Based Framework for COVID-19 Diagnosis Using Chest CT Scans and Clinical Information[J]. SN Computer Science, 2021, 2(5).

[4] Gupta Sonia, Agrawal Monika, Deepak Desh. Gammatonegram based triple classification of lung sounds using deep convolutional neural network with transfer learning[J]. Biomedical Signal Processing and Control, 2021, 70.

[5] Duong Linh T., Le Nhi H., Tran Toan B., Ngo Vuong M., Nguyen Phuong T.. Detection of tuberculosis from chest X-ray images: Boosting the performance with vision transformer and transfer learning[J]. Expert Systems With Applications, 2021, 184.

[6] Somu Nivethitha, Sriram Anirudh, Kowli Anupama, Ramamritham Krithi. A hybrid deep transfer learning strategy for thermal comfort prediction in buildings[J]. Building and Environment, 2021, 204.

ISSN: 2414-1895 DOI: 10.6919/ICJE.202109_7(9).0074

[7] Yang Dangfu, Wang Xiang, Zhang Haoran, Yin Zhen-yu, Su Dong, Xu Jun. A Mask R-CNN based particle identification for quantitative shape evaluation of granular materials[J]. Powder Technology, 2021, 392.

[8] Muller Bruno, Lengellé Régis. Cross-Gram Matrices and their use in Transfer Learning: Application to Automatic REM Detection using Heart-Rate[J]. Computer Methods and Programs in Biomedicine, 2021(prepublish).

[9] Yang Xiaodi, Yang Shiping, Lian Xianyi, Wuchty Stefan, Zhang Ziding. Transfer learning via multi-scale convolutional neural layers for human-virus protein-protein interaction prediction. [J]. Bioinformatics (Oxford, England), 2021.