Guest Editorial: Special Issue on Deep Representation and Transfer Learning for Smart and Connected Health

DEEP neural networks (NNs) have been proved to be efficient learning systems for supervised and unsupervised tasks. However, learning complex data representations using deep NNs can be difficult due to problems such as lack of data, exploding or vanishing gradients, high computational cost, or incorrect parameter initialization, among others. Deep representation and transfer learning (RTL) can facilitate the learning of data representations by taking advantage of transferable features learned by an NN model in a source domain, and adapting the model to a new domain.

Emerging and challenging domains such as smart and connected health (SCH), in which a lack of labeled data is a common problem, can greatly benefit from new theoretical advancements in RTL methods. For instance, RTL methods can overcome this limitation by training a model to learn universal data representations on larger corpora. Nonetheless, the use of RTL in developing SCH applications requires to overcome problems such as data set bias, NN coadaptation, and rejection of unrelated information. Other challenges arise due to the inherent tradeoff between retaining too much information from the input and learning universal features. Similarly, determining how to best learn a set of data representations that are ideal for a given task remains a challenge. Therefore, new theoretical mechanisms and algorithms are required to improve the performance and learning process of deep NNs by employing RTL methods.

This Special Issue provides a collection of state-of-the-art research works focused on theoretical aspects of RTL applied to the domain of SCH. After a rigorous review of 48 high-quality articles that were submitted, ten articles were selected for inclusion in this Special Issue. A brief summary of these articles is provided herein.

One of the main challenges in RTL is exploiting commonalities between tasks. In the article "Task similarity estimation through adversarial multitask neural network," Zhou *et al.* provide a theoretical perspective of the advantages of using information similarity for multitask learning. The authors continue by introducing a novel training algorithm to learn the task relation coefficients and automatically learn model parameters in adversarial multitask NNs.

Gu *et al.* also look at exploiting data commonalities in RTL. In their article "Deep graph-based multimodal feature embedding for endomicroscopy image retrieval," the authors propose a deep graph-based multimodal feature embedding framework for medical image retrieval, with application to breast tissue classification. In this graph-based model, the authors create similar and dissimilar pairs for probe-based confocal laser endomicroscopy (pCLE) and reference histology images. A Siamese NN is used to reconstruct the similarity between pCLE and the reference images to discover the latent feature space.

Yu *et al.* look at a multitask approach to deal with two modalities: magnetic resonance imaging (MRI) and computerized tomography (CT) scans. In their article titled "Multitask learning for estimating multitype cardiac indices in MRI and CT based on adversarial reverse mapping," the authors propose training a model to map multitype cardiac indices in MRI and CT to cardiac images. Their approach uses adversarial training to learn task dependencies through multitask learning networks. The model parameters learned using MRI images are transferred to a second model and fine-tuned for CT images, demonstrating excellent performance.

In scenarios where a lack of data is a common problem, data augmentation techniques are often employed to provide NNs with more data. This approach is known to help NNs provide a better generalization performance. Yet, the effect of data augmentation is often overlooked by the community. In the article "Deep learning for multigrade brain tumor classification in smart healthcare systems: A prospective survey," Muhammad *et al.* study the effect of data augmentation in transfer learning applied to brain tumor classification. The authors also provide an extensive review of contemporary state-of-the-art approaches to brain tumor classification, including available benchmark data sets.

In the article "Transformation-consistent self-ensembling model for semisupervised medical image segmentation," Li *et al.* also look at addressing scenarios where a lack of data is common. The authors propose using labeled and unlabeled data to learn data representations. In this semisupervised proposed approach, a NN is optimized by a weighted combination of a classification loss for the labeled inputs and a regularization loss for both the labeled and unlabeled data. The authors employ a student-teacher approach, in which the weights for the teacher model are a running average of the weights for the student model. The authors also employ a set of data augmentations to improve the model's robustness to rotation and scale invariance.

It is well established in the literature that an effective use of parameters learned by a given model in a different domain

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is a challenging task, particularly when the joint distribution of the input features and output labels is different in the target domain. In SCH, data is often very subject-dependent, causing drastic changes in the data distribution within the same domain. In the article "Deep representation-based domain adaptation for nonstationary EEG classification," Zhao *et al.* address this issue by treating multiple subjects as the source domain, and a single subject as the target domain. The authors apply this technique to electroencephalography classification, where data varies from subject to subject, causing a poor NN generalization performance.

Biometric traits are another example in which data are very subject-dependent. Subject-specific differences present a challenge for RTL given that the changes in data distributions from one subject to another can lead to a poor model generalization performance due to overfitting. In the article "Cross-subject and cross-modal transfer for generalized abnormal gait pattern recognition," Gu *et al.* propose a cascade of deep architectures that can encode cross-modal and cross-subject transfer for abnormal gait recognition. The success of the approach proposed by the authors relies on a multiencoder autoencoder architecture to disentangle subject-specific features from abnormal pattern-specific gait features.

Another challenge in SCH applications is the change in data distributions from one geographical location to another. An example of this is the prediction of gastrointestinal infection morbidity, which is heavily impacted by environmental pollution. In the article "Tridirectional transfer learning for predicting gastric cancer morbidity," Song *et al.* propose using mapping-based transfer learning to predict morbidity of diseases in various regions. To accomplish this, the authors use SCH data from a source region to try and predict the morbidity of a similar or different disease in a different target region. The authors propose a unified univariate regression and multivariate Gaussian model to establish relationships between two different diseases together with high-level pollutant features in the source region. The authors report promising results, which can help in improving medical preparedness and responsiveness.

Given the delicate nature of SCH applications, it is commonly desired to be able to process patient data in an effective manner and with minimal loss of information. This requirement, coupled with high computational cost, often makes it difficult to use portable equipment to process real-time data, resulting in delayed diagnoses. In the article "Handheld ultrasound video high-quality reconstruction using a low-rank representation multipathway generative adversarial network," Zhou *et al.* provide a great example of how RTL can help address some of these limitations by introducing a novel approach to enhance the video quality of handheld ultrasound devices. They propose a low-rank representation multipathway generative adversarial network to generate high-quality ultrasound video. The success of the approach is partly attributed to a new loss designed to acquire ultrasound-specific perceptual features, resulting in fine reconstruction of global and local details.

Understanding model performance in relation to the training data is an important task in representation learning. Yet, it is often overlooked in the literature. In the article "Neural encoding and decoding with distributed sentence representations," Sun *et al.* look at understanding the representations learned by deep distributed semantic models (DSMs) and their impact on model accuracy. The authors employ functional magnetic resonance images from humans reading sentences to evaluate the ability of DSMs to model brain activities. Sun *et al.* continue by investigating how the representations learned by DSMs can help explain the language processing of the human brain. Through a series of ablations studies, the authors show what features contribute the most to predicting and deciphering cortical activities in the brain.

The articles in this Special Issue demonstrate the challenging nature of SCH applications. They also highlight two main challenges for deep NN representation learning within the domain of SCH: lack of labeled healthcare data and poor cross-subject generalization. The works presented in this Special Issue propose deep RTL state-of-the-art solutions to such problems. Nonetheless, SCH is a newly emerging area of interest and many challenges lie ahead. This Special Issue aims to promote and encourage the development of theoretical methods in deep RTL in an attempt to help advance emerging and challenging areas such as SCH.

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