Latent Space Transformers for Generalizing Deep Networks

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***Abstract*—Sharing information between deep networks is not a simple task nowadays. In a traditional approach, researchers change and train layers at the end of a pretrained deep network while the other layers remain the same to adapt it to their purposes or develop a new deep network. In this paper, we propose a novel concept for interoperability in deep networks. Generalizing such networks' usability will facilitate the creation of new hybrid models promoting innovation and disruptive use cases for deep networks in the fifth generation of wireless communications (5G) networks and increasing the accessibility, usability, and affordability for these products. The main idea is to use standard latent space transformation to share information between such networks. First, each deep network should be split into two parts by creators. After that, they should provide access to standard latent space. As each deep network should do that, we suggest the standard for the procedure. By adding the latent space, we can combine two deep networks using the latent transformer block, the only block that needs to train while connecting different pretrained deep networks. The results from the combination create a new network with a unique ability. This paper contributes to a concept related to the generalization of deep networks using latent transformers, optimizing the utilization of the edge and cloud in 5G telecommunication, controlling load balancing, saving bandwidth, and decreasing the latency caused by cumbersome computations. We provide a review of the current standardization associated with deep networks and Artificial Intelligence in general. Lastly, we present some use cases in 5G supporting the proposed concept.**

***Index Terms*—Deep learning, sharing information, latent space, standardization**

I. Introduction

Recommendable advances in Machine Learning (ML) algorithms, computational capacities, processing, preprocessing techniques, and computer hardware have resulted in efficient training methods for Deep Neural Networks (DNNs). In addition, deep feedforward networks have recently provided enhanced acoustic modelling [1]. As a result, the number of use cases for the DNNs in varied fields will witness exponential growth in the future. Increasing demands will make processing time and techniques, parallel computing, and latency highly critical to the connected users. Technologies such as 5G- Ultra-Reliable Low Latency Communications (URLLC), edge, and cloud computing enable the development of applications using deep networks to provide high Quality of Services (QoS) for users with these needs. At the same time, researchers increase the utilization of the mixed deep networks to achieve better performance and higher accuracy. In addition, the innovations with computational techniques and training models will result in evolving neural networks.

To have seamless integration beyond the fifth generation of wireless communications (5G) networks and deep hybrid networks have some open challenges. Standards support innovations, research organizations to build new training models and network architecture to facilitate enormous data and processing capabilities. It is speculated that standardization on latent space will boost research activities towards innovative hybrid networks with reduced or no retraining requirements. Latent spaces define the data representation in another domain space. For instance, it is the space that resulted in modifying some data features like the mathematical transformations. For example, selecting, extracting, and transforming to new domains happens automatically in deep networks, and there are no rules on the number of layers and units per layer. However, because these variables are hyper-parameters and based on the performance achieved. Thus, we propose to use the latent space to reduce the amount of retraining by separating deep networks. The contributions of this paper are the following:

1) A concept for sharing information between several trained deep networks from different fields (e.g. text and speech and images, resource allocation and security algorithms and, others) is able to decrease latency and computation requirements in deep networks applications reducing training processing costs;
2) New concepts for training techniques to create hybrid networks from pretrained networks;
3) New transfer learning methods for using pretrained deep networks with small datasets.

This paper is organized as follows. Section II discusses the state-of-the-art and Section III presents the standardization activities concerning the AI, ML, and deep networks. Section

IV provided limitations of state-of-the-art associated with standardization activities, and Section V addressed the novel concept of reducing the retraining activity and proposes the new concept for sharing information between deep networks. Section VI discusses an integrated view between the proposed idea and the uses cases for 5G networks. Finally, Section VII presents the main conclusions of this work.

II. State-of-The-Art

Artificial Neural Networks (ANN) are networks of connected nodes guided by the associated weights to facilitate the implementation of Artificial Intelligence (AI) to solve real-life problems. ANNs are useful in designing prediction models, automation and control, and applications requiring trained datasets to make decisions or identify patterns. ANNs are adaptive to the learnings from the information they carry. This information is processed using mathematical/ computational models. The nodes are assembled into layers that perform transformation operations to the inputs [2]. Information travels through multiple layers. ANNs are trained by adapting to network parameters and environment. There are various ways to train a network, for example, supervised learning, unsupervised learning, reinforcement learning, self-learning and, so on [3]. Deep Learning (DL) is an approach where the network observes, identifies, and learns the representations required to process and categorize the raw data. A multi-layered ANN capable of modelling complex linear or non-linear relationships is a Deep Neural Network (DNN). DNN formulates compositional models from the structured or unstructured input datasets and extracts features from different layers. These networks are well-versed to create approximate models with the provided data input. The data flow from the input layer to the output layer, and thus, these networks are also called feedforward networks.
The flow of data can be expressed as follows;

1) The weights of neurons in a DNN is initialized by the random numbers.
2) The output is generated using the activation function after multiplying the inputs with the associated weights.
3) An optimization algorithm will update the weights if the desired accuracy is not achieved.

A. *Hybrid Deep Networks and Sharing Information*

The researchers mention two kinds of hybrid deep networks in the literature—the combination of one deep network followed by machine learning algorithms such as Support Vector Machines (SVMs). For example, in [4], the hybrid combination of Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) with SVM is compared to achieve higher accuracy for sentiment analysis. In different methods like in [5], several deep networks such as CNN, LSTM, Bidirectionally Long Short-Term Memory (BiLSTM), Gated Recurrent Unit (GRU) were used separately to extract the features, and by concatenating all of these features followed by the Softmax layer, the hybrid network was created and was used for sentiment classification. In another way of the combination of deep networks as a series, one followed after another like [6], the authors for analysis Human Activity Recognition (HAR), used the CNN network followed by another RNN network type, e.g., LSTM, BiLSTM, GRU, and Bidirectional Gated Recurrent Unit (BiGRU). In the other fields, such as security, we were using hybrid deep networks increasing. Another hybrid method was used in [7] for attack detection in the Internet of Things (IoT). As in [6], they used the LSTM network after extracting futures by the CNN network. The recent researchers proved that using hybrid deep networks can improve the performance in many different use cases.

This paper proposes a new concept for standardization related to sharing information between the deep networks without changing the last layers, developing a new individual network, or retraining the pretrained networks. Standards for deep networks are critical because several fields use such networks nowadays (e.g., health, telecommunications, gaming). With standardization, the use cases of deep networks are publicly available, which promotes dissemination and broad application. Furthermore, standardization helps prevent market fragmentation, which inhibits growth, and mutually incompatible solutions are avoided.

III. Standardization Activities

Standards are essential to driving research, innovations, policymakers, and industries. They form a set of guidelines that validate requirements specifications and assure quality [8]. In addition, they align various approaches to have interoperable solutions as we are advancing every day with technology and its vast usages.

There are different types of Standards Development Organizations (SDOs) working towards standards for AI applications. SDOs are categorized at International, National, and Regional levels. Some of the renowned SDOs are ISO (International Organization for Standardization), IEC (International Electrotechnical Commission), ITU (International Telecommunication Union), European Telecommunications Standards Institute (ETSI), etc. In addition, organizations like the 3rd Generation Partnership Project (3GPP), Institute of Electrical and Electronics Engineers (IEEE), and oneM2M are examples of Standard Initiatives groups that collaborate and coordinate standardization efforts on different subjects [8].

A. *Standards in Artificial Intelligence*

Table I summarizes some of the ongoing standardization initiatives concerning AI/ML architectures and techniques. For the AI ecosystem, standards and specifications are indispensable as they ensure a safer and reliable future. Furthermore, the connected, intelligent devices generate enormous data and the information required for the training models. Furthermore, data is critical and essential in intelligent environments as they include personal as well professional details. For instance, in healthcare scenarios, data cannot be shared or used for training purposes [20]. Thus, it is of utmost importance to have a specified requirement to regulate data

TABLE I
STANDARDIZATION ACTIVITIES CONCERNING AI/ML/DL

	Standards	Summarized Activities
1	IEEE P2830, Standard for Technical Framework and Requirements of Shared Machine Learning ITU T Y.3172 [9]	This standard defines the framework and architecture for the training model using multi-source encrypted data in a trusted third-party environment. Its emphasis is on the use of a third-party execution environment to process encrypted data. The standard intends to provide a verifiable basis for trust and security and outlines functional components, workflows, security requirements, technical requirements, and protocols.
2	P3333.1.3/D2-IEEE Draft Standard for the Deep Learning-Based Assessment of Visual Experience Based on Human Factors [10]	This standard is dedicated for defining deep learning-based metrics of content analysis and quality of experience (QoE) assessment for visual content. It targets to contribute to an enhanced user experience. To achieve high QoE, this working group is focused on areas concerning perceptual quality and virtual reality (VR) cybersickness. Its DL models count for affecting human factors, reliable test methodology and a database construction procedure. It also defines cases for deep analysis of clinical and psychophysical data, deep personalized preference assessment of visual contents, and building image and video databases.
3	Focus Group on Machine Learning for Future Networks including 5G (FG-ML5G) [11]	FG-ML-5G is an ITU-T Study Group 13 (SG13) Focus Group on Machine Learning for Future Networks including 5G. It has documented 10 technical specifications for ML for future networks, including interfaces, network architectures, protocols, algorithms, and data formats. It was active from January 2018 until July 2020. Following are some of the relevant contributions from this focus group concerning the proposed work. 1) ITU-T Y.3172: Architectural framework for machine learning in future networks including IMT-2020. 2) ITU-T Y.3173: Framework for evaluating intelligence levels of future networks including IMT-2020. 3) ITU-T Y.3174: Framework for data handling to enable machine learning in future networks including IMT-2020. 4) ITU-T Y.3176: ML marketplace integration in future networks including IMT-2020. 5) Serving framework for ML models in future networks including IMT-2020.
4	ITU-T Y.3172 [12]	ITU-T Y.3172 provides an architectural framework for machine learning in future networks including IMT-2020. It specifies a set of architectural requirements, components and, their integration guidelines. It defines an ML pipeline, ML management and, orchestration functionalities.
5	ITU-T Y.3173 [13]	ITU-T Y.3173 specifies a framework for evaluating the intelligence of future networks including IMT-2020 and introduces a method for evaluating the intelligence levels of future networks including IMT-2020. It defines an architectural view for evaluating network intelligence levels based on the recommendation in ITU-T Y.3172.
6	ITU-T Y.3174 [14]	ITU-T Y.3174 Framework for data handling to enable machine learning in future networks including IMT-2020. It describes the requirements for data collection and processing mechanisms in various usage scenarios for ML and drafts a generic framework for data handling and examples of its realization on specific underlying networks.
7	ITU-T Y.3176 [15]	ITU-T Y.3176 provides ML marketplace integration in future networks including IMT-2020 and provides a high-level requirements and the architecture for integrating ML marketplaces based on the requirements in ITU-T Y.3172.
8	AI Ecosystem Standardization Program at the European Commission Workshop [16]	IEC and ISO organized a workshop on the AI Ecosystem Standardization Program to fully exploit the potential of AI across Europe and guarantee Europe's leading position in AI. It summarizes varied initiatives in individual EU nations and provides an initial snapshot of the European AI landscape.
9	Securing Artificial Intelligence [ETSI GR SAI 005) [17]	ETSI GR SAI 005 focuses on deep learning and explores the existing mitigating countermeasure attacks. It describes the workflow of machine learning models where the model life cycle includes both development and deployment stages.
10	ITU-WHO FG AI4H [18]	The ITU/WHO Focus Group on Artificial Intelligence for Health focuses on creating a standardized assessment framework for AI methods in health. The FG constitutes members from various research organizations, government agencies, healthcare facilities, and many more. FG AI4H is a joint initiative from ITU and World Health Organization (WHO).
11	ITU-WHO FG AI4NDM [19]	The ITU/WMO/UNEP Focus Group on Artificial Intelligence for Natural Disaster Management (NDM) focuses on establishing a roadmap for an effective and secure use of AI methods for NDM. The FG activities include data collection and handling, improving modelling across spatiotemporal scales, and providing effective communication.

sharing and analysis. IEEE is working towards the Ethically Aligned Design for AI [21], and also European Union's (EU) General Data Protection Regulation (GDPR) [22] sets regulations on how the data can be used. AI and ML is an extensive and open area where the details at each level are crucial.

IV. SHORTCOMINGS

In the following, we summarize the limitations in the current standardization related to deep networks, which motivate us to propose new standards related to sharing content between such networks.

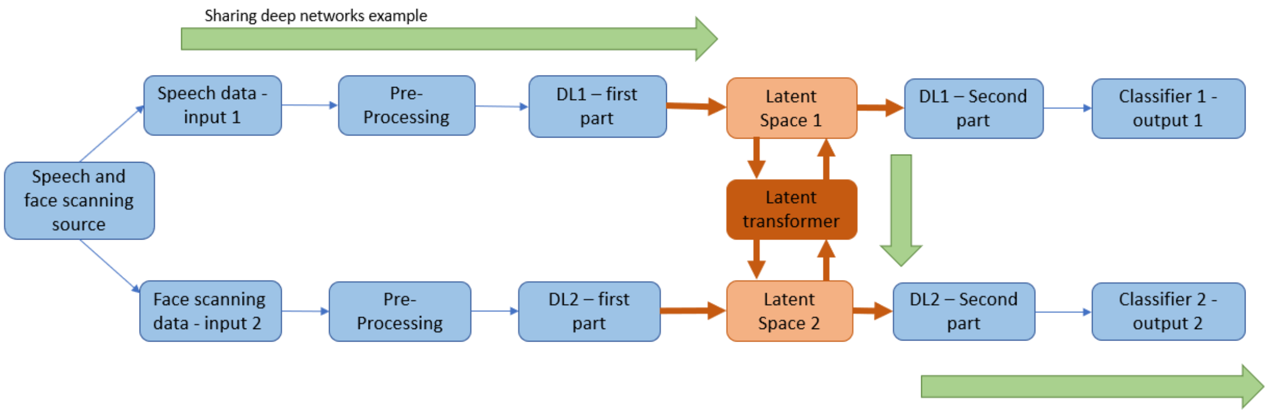

Fig. 1. Latent Transformer to Mix Two Deep Networks with Different Purposes (e.g. speech and face scanning)

A. *Limitations on the State of the Art*

There are limited algorithms like SVMs supported by a solid mathematical background in machine learning and deep networks literature. However, these methods still need user intervention in selecting some hyper-parameters such as kernel-trick mode or the value of regularization, which are difficult to define in deep networks. These parameters are tuned commonly by grid searching on all possible domain values. This limitation causes the training of deep networks to be computationally costly for researchers, and improving the deep networks is possible for only a few organizations or labs that have access to enough hardware and data resources. Based on this lack, the methods like transfer learning were invented to retrain the pretrained deep networks by the new small datasets used by different researchers. However, these replacement methods suffer from complexity and also low compatibility with new other datasets. Based on the number of samples contained in each new dataset and the similarity between the original dataset used to train the deep network and the new dataset, which will be used on the same network, this complexity can be varied. It can cause to change only a few last deep network layers and train only them, or retrain the whole deep network.

B. *Limitations on the Standards*

Studying various standardization activities concerning AI and ML, few standards are available for defining the architecture for preprocessing data and preparing them for machine learning algorithms. Also, there is some guidance for using different blocks and techniques in the typical programming frameworks like Pytorch or TensorFlow for deep networks. However, improving the performance of deep networks needs some standardization beyond the existing ones. The two usual ways for enhancing the existing deep networks are using more data or adding more layers. Nonetheless, methods such as distillation may help reduce the size of deep networks, but they are not enough. Therefore, new standardization needs to separate Deep networks into independent parts. These parts enable researchers with low resources to use the parts, improving or replacing parts of their networks without training. In addition, the combination of different trained parts from several deep networks will be provided.

V. Proposed Idea

According to [23], latent space is a different domain space where data can be decreased to represent new optimal features adequately. The new features may be more distinguishable per each class which facilitates solving classification problems. Typically, when we modify data features, such as some mathematical transformation, those features will be converted to another domain known as latent space In deep networks, features selection and extraction happen automatically. After each layer, the features are converted into a new domain known as latent space. There are no rules on the number of layers and units per layer. Moreover, the result of each layer may depend on the data availability.

Both the number of units and layers are hyper-parameters and, based on the performance achieved in results, will be changed and are varied from one researcher to another. The concept of separating deep networks into at least two parts is to access latent space defined by a specific standard. However, this latent space should follow some rules and standards, and the number of network layers before it should provide some required quality. A practical example of this idea can be the deep hybrid networks using the encoder parts of autoencoders to transfer features in the new latent space, but not standardized, and then feeding to another deep network.

This specification offers a new level of generality for the latent spaces and the network layers before and after them. In addition, these parts of deep networks will be made reusable without needing retraining by the new dataset. By doing these changes, new transfer learning techniques will emerge, and interoperability between deep networks with different datasets will be possible.

Figure 1 depicts the procedure to mix two deep networks with different purposes (e.g., speech and face scanning) by only training the latent transformer unit, using the elements of two deep networks with the different tasks using the latent transformers. The arrows include the process steps and the parts which were chosen from each deep network. In the first path, the source generates speech data, followed by pre-processing. It is fed in the first part of the deep network - DL1 and then converted to latent space1. Traditionally, the data would be fed to the second part of the deep network 1 - DL1 and, after classification/regression, we would be able to see the results. The face-scanning data would follow the same method in input 2 toward the deep network 2. Using standarized latent spaces, the latent transformer block could convert data from one latent space to another. This conversion makes it possible to create two other paths using the first part from one network and the second part from another network, as highlighted in Figure 1. Using latent transformers and conversion from one latent space to another enables multiple types of data accepted as input or be created as output. By dividing the pipeline into small parts and replacing only some elements may improve the performance and accuracy of the whole process significantly because the raw data is pre-processed and prepared in the deep network's first part. Furthermore, adding new features and maintenance may be more accessible. Besides mixing both networks, we can create mixed data, increasing the feeling analysis. This new technique also works for parallel-connected deep networks. For example, in the ensemble technique, only the first part of each network needs to be used. By ensemble latents, the amount of prediction calculation in ensembling methods will be expected to decrease because there is no need for the second part of the networks while the final performance increases. It causes the latency prediction of networks also to be improved. A critical implementation of standard latent spaces is providing information sharing and transforming between different deep networks. The idea is that instead of training networks for particular purposes, we can use the combination of general networks, and only the transformer units between them should be trained. It will be happening by generalization provided by standardization of latent spaces in deep networks under the same framework.

The importance of using parts of one deep network combined with the elements of another deep network will be revealed while enough edge computation or bandwidth will not be available for the users. In this situation, the different latent spaces of deep networks with various fields produce different data sizes in latent space. So, this combination can make the same result but with lower edge computation or bandwidth for transferring.

With this standard related to latent spaces available in the research community and between European countries, the ability to use the series of deep networks by using latent transformers will be possible. It makes the complicated tasks more manageable than before, which concludes the integration of multi-services. For example, by combining different elements of deep speech transcription, deep translation, profound text to speech, and finally, deep fake technology, we can have the users from various countries and languages communicating their native languages. It is only one example of how we can, with less effort, facilitate the interaction between humans in real-time. To achieve this, the latent transformers need to be trained and create the required compatibility. This process also can make the new generation of transfer learning for deep networks. Recording data of one latent space can further be analyzed by other techniques and deep networks later.

VI. Generalization of Deep Networks in 5G Communications

Deep Networks generalization by standards in Research and Development (R&D) reduces training processing costs, increases investment in security, provides an innovative solution with information advantage over future competitors in 5G markets and provided experience exchange with essential participants in the standardization process. Thus, standardization generates innovation, expands business access, and internationalizes new technological advances.

The development of the telecommunication systems 5G coincides with the emergence of the IoT, extended reality new use cases, and improvements in deep learning techniques, leading to the development of applications combining them in the future to provide high Quality of Services (QoS). Therefore, it affects accessing the high bandwidth with low latency will be required more than before, and cause to creating the massive amount of transferred data from the edge to cloud for processing. Splitting deep network parts between edge and cloud and transferring the represented latent data can provide a new opportunity for developers to create and improve the new cloud services based on the standard latent domains for deep networks.

Conversion data into common latent space should happen on the edge side to remove the redundancy from data, decrease the data dimension, and apply the super compression techniques as illustrated in Figure 2. The deep network that implements resource allocation algorithms is integrated with the security in the edge using latent spaces transformers and the neural network processing computes the result of the mixed deep network in the cloud. These steps of data reduction followed by the existing or new security standards can provide a high level of personal data protection without significantly increasing the amount of final data rather than the initial for transferring to the cloud. Also, other deep networks related to resource allocation and security techniques can be merged creating, a new secure, optimized algorithm. This process is expected to create an innovative competition between several industries to improve and create better standards for latent spaces or improve the following parts based on the existing latent standards.

In the future, we envisage that a latent space with high quality of service will be a commodity that people will rent or buy to provide services. Hence, we can expect different versions of latent spaces with various QoS requested by the users or the available network bandwidth. This concept also fits the described solution to be compatible with different network bandwidths.

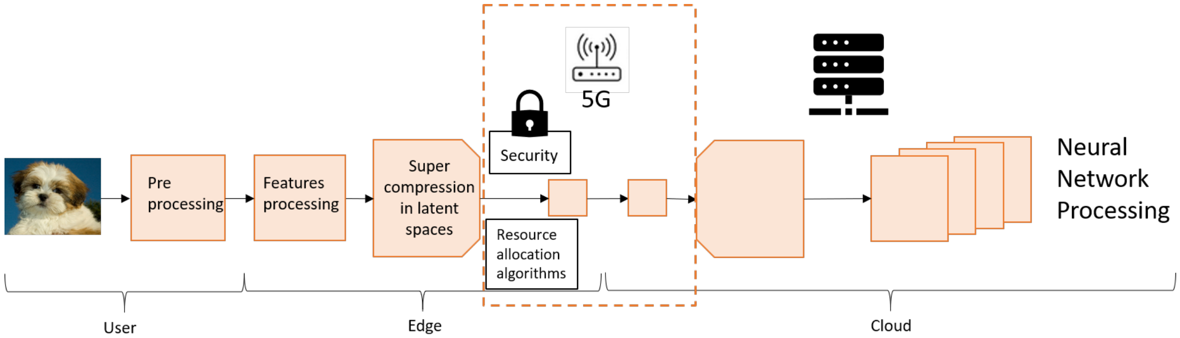

Fig. 2. Use Case for 5G using Deep Networks

VII. Conclusions

Generalizing deep networks by sharing information between them using latent transformers may reduce the costs of the training process. This generalization can be implemented throughout standardization. Additionally, it might create an opportunity for innovation by combining pretrained deep networks to generate other hybrid networks for new purposes, research, and development. There are several standards available for Artificial Intelligence and Deep Learning. However, none of them considers the possibility of using latent transformers blocks for sharing information. Unfortunately, the standards activities are not public, so researchers do not have easy accessibility to all developments and proposed frameworks. Therefore, at this point, assuming the area that we are covering is not in the standards, it is an open research area, and we propose the requirements and related guidelines to develop our concept. Moreover, we showed several use cases applications for this standard (e.g., processing image and sounds, mixing security and resource allocation algorithms in 5G networks and IoT devices, ensembling multiple deep networks and extended reality scenarios).

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