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Short Communication

Impact of Deep Neural Learning in Computer Science

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Earlier trends in computer science introduced symbolic AI as a giant leap in machine intelligence. Emphasis was on how machines can be programmed to perform human tasks. Symbolic AI is a program written which takes specific inputs and produces the intended outputs using a set of pre-determined rules. It makes symbolic AI a task-specific program, and we need to write a different set of rules for the different tasks. Gradually researchers shifted their focus from task-specific programs to define learning models that can be used for various tasks. A subfield of AI, called Machine Learning, started emerging where the focus is on training the models for knowing the patterns hidden in the data. These patterns are nothing but the rules that can be used for making predictions on unknown data samples. With the advent of the internet, a tremendous amount of data started generating and increased processing capabilities. It forced research communities to dive into deep neural networks and invent newer, more sophisticated neural models to understand the data more accurately. A deep neural network does so by providing detailed representations of the input data using its layered architecture. At each next layer, more details are analyzed and represented. Thus deep neural networks are a subdomain of machine learning with much more capabilities.

Technological advancements with deep neural learning are making the tasks of autonomous robots, cars, natural language systems like Amazon's voice assistant Alexa, Apple's Siri, Microsoft's Cortana, object recognition tasks such as face recognition are possible. Convolutional neural networks are the promising ones that remove the burden of manual pre-processing of images or videos. Deep neural learning is a supervised learning approach where data with pre-known outcomes is fed to the system to generate a model. This model is then used to check its viability for the data with unknown outcomes. The outcomes in known environments are also called labels. The data samples with known labels are known as a training set, while those without labels are known as a test or validation set. In particular, a model is learned on the training set and validated on the test set. A deep neural network follows a layered architecture. Input is also fed in a layered fashion, and this layer is called the network's input layer. Each subsequent layer in the network contains many separate neural computing units. Weighted inputs are equally fed to all these computing units in the next layer. A bias term is then added to these inputs to take into account any uncertainties. The primary difference between deep learning and machine learning is its capability of modeling non-linearity using activation functions and an automated feature engineering process. The input passes through the activation function at each neural computing unit to account for any non-linearity present. At each pass, the output produced by the deep network is compared with the true labels, and the difference between them is calculated using some loss function. This one-way process of producing outputs from the given inputs is known as the forward pass of the network. As a part of training, the loss computed at the end of each pass must be used to optimize the network parameters. This process is often called a backward pass of the network, and its aim is to update the weights to reduce the loss function. Backward pass makes use of some optimizers like gradient descent and its variants. In the end, to measure the performance of your network a metrics like accuracy for discrete-valued outcomes and mean squared error for continuous-valued outcomes.

Deep learning has covered almost every sub-domain of computer science, such as computer vision, natural language processing, object detection & recognition through image/video, robotic path planning, and many more. With the advent of GPUs and TPUs, more variants of deep architecture were introduced. These variants were initially developed to meet the famous Imagenet challenge. Later on, researchers found these models very useful as pre-trained networks for transfer learning functions. Many of these models are available through the open-source API of Keras Library. To name a few, François Chollet's Xception [1], Oxford's VGG Net [2], Microsoft's ResNet [3], Google's Inception [4], Mobile Nets [5] for mobile applications have spanned significant research domains. In transfer learning, these pre-trained models are directly used with initially trained weights, and later on, as per the current research demands, these parameters are tuned. Many new architectures like Generative Adversarial Networks (GANs) [6] are in place to meet the demands of high voluminous data with only a few initial samples available. Deep transformer [7] architectures are introduced to deal with complex Natural Language Processing tasks.

Incredible advancements in deep neural architectures, high computational capabilities, ubiquitous and scalable infrastructures make deep learning one of the favorite choices for researchers.

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