Ass # 01 NLP
7B

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02-131212-049

Q1 Learning Representations by Back propogation of Errors by David E. Ramelhart, Greoffery E hinton, and Ronalt J. Williams

Abstract:

In this article back propogation "sys" was introduced, an essential method for train an artificial neural networks, essentially its a multilayer perceptions. This algorithm enable efficient computation of the gradient of the error function and allows for adjusting the weight within Neural network.

Introduction: In this article the author discuss the limitations of early Neural Networks, which faced hardness to learn complicated functions due to the lack of an effective way to update hidden layer weight. The given Solution is an algorithm that enables neural networks to learn from data by calculating the error at the output and propogating this error backward through network.

Back propogation Algorithm: It applies the chain rule to calculators to Compete the gradient of the error function with respect to the weights in each layer of the network., It envolve a forward pass to Compute the output and a backward pass to Compute the gradients.

The network weights are adjusted using these gradients to minimize the error between predicted and real values.

Applications:- The paper highlights the successfull application of backpropagation in pattern recognition, speech recognition and image classification tasks, demonstrating the power of multi layer neural networks in handling complex real-world problems.

Experiments and Results:-

Various experiments confirm the efficiency of backpropagation in training networks to recognize hand written digits and other classification tasks. It was found to perform other techniques in handling high-dimensional data with minimal pre-processing.

Conclusion:

The backpropagation algorithm revolutionized neural network training, allowing for deeper networks and more complex task to be handled effectively, setting the foundation for further advancements in neural network and ML.

2) Deep Learning by Yann Lecun, Yashua Bengio and and Geoffrey Hinton.

Abstract:

This review paper explores the rise of the deep learning, a class of ML methods that utilizes multilayer networks to automatically learn data representations. The paper highlight deep learning success in numerous fields, including computer vision, speech recognition and NLP

Introduction: In this article the author discuss the limitations of traditional ML, which required hand-crafted feature engineering. Deep learning, by contrast, enables the automatic discovery of hierarchical representations which capture increasingly abstract features as data progress through network layer.

Supervised learning: The most common deep learning approach, supervised learning involves training models on labeled data. The network computes an output for each input, which is compared against the true labeled. The model improves as it processes more labeled data.

Key Architectures: In this article the author review two key architecture

1) CNN for image processing and
2) RNN for sequential data such as text and speech.

CNN automatically extract features from raw pixel data,
while RNNs are ideal for tasks where the sequence of input matters.

Applications:-

Deep Learning has been transformative in many domains, particularly in tasks involving high-dimensional data. The paper discuss breakthroughs in image and Speech recognition, language understanding, genomics and drug discovery. Deep learning has enabled machine to outperform previous methods in task like image classification.

Challenges:-

Despite its success, deep learning requires substantial computational resources and Large ds for effective training. The author suggest the Future advancements will likely come from unsupervised learning and reinforcement learning. which Could allow for more efficient and flexible models.

Q3 The forward forward Algorithm : some preliminary Investigation by geoffrey hinton.

Abstract:- The paper introduces the forward forward (FF) algorithm, a novel learning procedure for neural networks that replicates back propogation. Instead of propagating errors backward. The FF algorithm uses two forward process one. with positive (real) data and the other with negative data the goal is to optimize a goodness function for each layer

Introduction:- hinton discuss the limitations of back propation, particulary in its biological. and Computational ineffeciencies. The FF algo is proposed, as a more biologically plousible alternative that can learn in real-time without needing to store activities for backward error propogation

The Forward Forward Algo:-

The FF algo involves two forward passes, one with real data to maximize the layer goodness and another with negative data to minimize it. this learning method eliminate the need for the backward pass of back propogation, making it more suitable for certain application like low power hardware

Experiments:-

The paper present premilinary experiments demonstrating that the FF algorithm works effectively on small problems like MNIST digit classification. Howeve the FF algorithm doesn't generalize as well as back propagation on larger problems, and it is slower. Despite these limitations, it shows promise for furture research in biological learning models and low-power systems.

Conclusion:-

~~It~~ Although the FF Algo is not likely to replace back propagation for large scale apps, it offer a biologicall plausible alternative for certain models. Furture research is needed to explore its potential, especially in hardware implementation and unsuprvised learning scenerios.

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