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Meeting Summary for Deep Learning Lectures

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Meeting summary for Deep Learning Lectures (02/10/2025)

Quick recap

Chinmay led a lecture on the back propagation algorithm in training neural networks, emphasizing the importance of understanding its functionality and the use of GPUs in modern deep learning. He also discussed the SD algorithm, gradient computation in neural networks, and the implementation of gradient descent for a neural network. The conversation ended with discussions on the complexities of neural networks, the concept of partial derivatives, the evolution of neural networks and their training, and the potential for further innovation in GPU technology.

Next steps

• Students to complete homework 1 by the deadline in 2 weeks.
• Chinmay to post additional reading material on GPUs and deep learning history.
• Chinmay to confirm by email if class will meet on Tuesday next week due to potential holiday schedule.

Summary

Chinmay's Lecture Amidst Health Concerns
Chinmay initiated a lecture, despite being unwell and experiencing audio issues. He expressed concerns about his health and the quality of the audio, but proceeded with the lecture. The main agenda for the day was discussed, but the details were not provided in the transcript.

Back Propagation and GPU Training
Chinmay discussed the importance of understanding the back propagation algorithm in training neural networks. He emphasized the need to derive the algorithm in detail to understand its significance and functionality. Chinmay also introduced the concept of using GPUs in training neural networks, explaining their importance in modern deep learning. He reminded the participants about the homework due in two weeks and

stressed the importance of original work and timely submissions. He encouraged the use of resources and collaboration but emphasized that the final work should be the individual's own.

Gradient Computation in Neural Networks
Chinmay discussed the SD algorithm, which updates weights in the negative direction of the gradient. He also mentioned the homework deadline and the grading system. The main focus of the meeting was on the gradient computation in neural networks. Chinmay explained that the gradient is a long vector as big as the number of parameters in the neural network. He emphasized the need for an efficient gradient computation algorithm, which led to the discussion of the back propagation algorithm. He used a simple example of a single neuron with a single feature over a single data point to illustrate how the back propagation algorithm works.

Gradient Descent for Neural Networks
Chinmay discussed the implementation of gradient descent for a neural network. He explained the process of computing the gradient, which involves taking the partial derivative of the loss function with respect to the parameters. He also highlighted the inefficiency of manually computing the gradient, as it involves repeating computations multiple times. Chinmay emphasized that this approach is not suitable for large-scale neural networks with millions of neurons and parameters. He hinted at the existence of an alternative method, which he promised to discuss in future sessions.

Dynamic Programming in Neural Networks
Chinmay discussed the concept of dynamic programming and its application in reducing repeated computations in algorithms. He explained how the structure of a neural network can be exploited to avoid repeating computations, using the example of a simple neural network. Chinmay then introduced the concept of a computation graph, which represents the arithmetic operations within a neural network. He clarified that a computation graph is a directed acyclic graph (DAG) and that it is not a chain rule. The discussion ended with the understanding that the concept of a computation graph can be extended to larger neural networks with millions of neurons.

Efficient Derivative Computation With Back Propagation
Chinmay explained the algorithm for computing derivatives efficiently using the computation graph, known as back propagation. The algorithm consists of two steps: a forward step and a backward step. The forward step involves instantiating the flow of information from left to right in the computation graph, with each node's value being computed based on its parents. The backward step involves computing the partial derivative of the loss function (L) with respect to each variable (Vj) in the graph, using the chain rule. This is done by summing the partial derivatives of L with respect to each child (Vj) of the variable, multiplied by the partial derivative of Vj with respect to the variable. The process is repeated for all nodes in the graph, starting from the last node (L) and moving backwards. Chinmay also clarified the forward pass, which involves assigning values to each node in the graph based on the values of its parents.

Calculating Partial Derivatives in Neural Networks
Chinmay guides the group through the process of calculating partial derivatives in a neural network's backward pass. He explains how to compute the partial derivatives of the loss function with respect to various components, including L, U, Z, W, and B. Chinmay emphasizes the importance of reusing previously calculated values and

applying the chain rule where necessary. He also clarifies that partial derivatives with respect to constants can be ignored.

Understanding Backpropagation in Neural Networks
Chinmay explained the concept of backpropagation, a method used in neural networks to simplify gradient computation. He emphasized that backpropagation doesn't solve all problems, but rather makes gradient calculation easier by exploiting the structure of the neural network. He used a simple example to illustrate how backpropagation works, highlighting the importance of parent-child relationships in the computation graph. Chinmay also clarified that the backpropagation approach is the same for both RNNs and CNNs. He concluded by mentioning that the algorithm is widely used in Pytorch and other network training tools.

Neural Networks Complexity and Computation
Chinmay discussed the complexities of neural networks, specifically focusing on the concept of multiple neurons and the computation graph. He explained the forward pass, which involves instantiating values based on the values of its parents, and the backward pass, which involves computing the derivative of the loss with respect to all intermediate variables. He emphasized the importance of understanding the chain rule and the dot product in these processes. He also mentioned the concept of a dense neural network, where every neuron in a layer is connected to every neuron in the next layer. The discussion was aimed at making the concept of neural networks more complex and challenging for the participants to understand.

Understanding Neural Network Computations
Chinmay discussed the concept of partial derivatives in the context of neural networks. He explained that the flow of information in the backward pass can be reduced to matrix operations, specifically through the application of local Jacobians of the network operations. He emphasized that both the forward and backward passes in a neural network involve heavy computations that are essentially matrix vector multiplications. Chinmay concluded by highlighting the significance of this understanding, as it simplifies the complex computations involved in neural networks.

Gaming and Graphics Processing Units
Chinmay led a discussion about gaming and graphics processing units (GPUs). He noted that many in the class were gamers and asked them to name their favorite games. He then explained why GPUs are essential for gaming, particularly for graphics-heavy games. He explained that GPUs are designed for parallel processing, which is perfect for matrix computations, a key component of graphics rendering. He also mentioned that GPUs became more accessible around 2005, leading to a significant improvement in game graphics quality. The discussion ended with Chinmay emphasizing the importance of matrix computations in gaming and the role of GPUs in accelerating these computations.

GPU Evolution and Neural Network Training
Chinmay discussed the evolution of neural networks and their training, highlighting the role of GPUs in making deep neural networks feasible. He explained that until the 2000s, training deep neural networks was challenging due to the difficulty of gradient computations. However, with the advent of GPUs, which are perfect for matrix operations, deep neural networks became more accessible. Chinmay also mentioned the trade-offs involved in using GPUs, such as memory limitations. He concluded by outlining the topics for the next few weeks, including convolutional networks and recurrent neural networks,

and emphasized that the only algorithm needed for training these networks is backpropagation. The class also briefly discussed the potential for further innovation in GPU technology.

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