LEARNING INTERNAL REPRESENTATIONS BY ERROR PROPAGATION

1. Analysis of the paper:

The paper basically marks the origin of backpropagation algorithm and discusses about building neural networks that can develop an internal structure appropriate for a particular task domain, building neural networks capable of learning representations by using hidden layers.

If the input is directly connected to output unit, it is easy to find learning rules that iteratively adjust the weight to reduce the difference between the actual and desired output. And such networks map similar inputs to similar outputs but a network with this constraint will fail to perform certain necessary mappings. (Ex: XOR).

If there are right connections from the input units to a large enough set of hidden units, we can always find a representation that will perform any mapping from input to output through these hidden units.

Back-propagation is an algorithm that allows us to build and train neural networks with hidden layers. The learning procedure decides under what circumstances the hidden units should be active in order to achieve the desired input-output behavior. The hidden units are going to learn to represent some features of the input domain.

They propose the algorithm:

1. Get linear function of the state of neuron. $\mathbf{X_i = \sum Y_i W_{ji}}$
2. Then, calculate the output of that layer by using non-linear function. $\mathbf{Y = 1/1+e^{-x}}$ (Sigmoid function or any function with has a bounded derivative will do).
3. We must find a set of weights such that for each input the output is same as desired output. The total error in the performance of the network with a particular set of weights can be computed by comparing the actual output and what network calculates.
4. To minimize E by gradient decent, it is necessary to compute the partial derivative of E with respect to each weight in the network. This procedure is termed as backward pass.
5. After computing derivative of E, we can find the other derivatives by using chain rule. This means that we know how much a change in the total input (or any other unit in network) to an output unit will affect the error. Then, change each weight by an amount proportional to the accumulated derivative of E with respect to W.

The gradient decent is not guaranteed to find a global minimum. They found this sort of undesirable behavior in networks that have just enough connection to perform task. Adding few more connection, adds a new dimension which provide paths around the local minima. They summarize that this learning procedure**,** is not feasible model of learning in brains. However, applying the procedure to various tasks shows that internal representations can be constructed by gradient decent in weight-space, and this suggest that it is worth looking for more ways of doing gradient decent in neural network.

2. **What I liked about this paper.**

   This paper was easier to read, understand and relate to the backpropagation algorithm, it basically proposed the idea of this algorithm and they describe the problems using examples and their results which makes this paper interesting.

   What I liked more about this paper is the number of problems they tried their proposed study on. They discussed about their future plans and works, and this Is how I expect the research to be.

3. **What I did not like about this paper.**

   To be honest I enjoyed reading this paper and there was nothing that I disliked in this paper. The only thing that comes to my mind is that I felt that they were not optimistic about the great work they did, after every example or problem they kept writing that the learning algorithm needs to be trained on complex problems or they need to study and work more.

4. **Inspirations from this paper:**

   The backpropagation algorithm was originally introduced in the 1970s, but its importance was not fully appreciated until this paper by David Rumelhart. This paper describes several neural networks where backpropagation works far faster than earlier approaches to learning, making it possible to use neural nets to solve problems which had previously been insoluble. Today, the backpropagation algorithm is the workhorse of learning in neural networks this is an inspiration.