Rumelhart et al. Analysis

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In the paper *Learning Internal Representations by Error Prorogation*, David E. Rumelhart, Geoffrey E. Hinton, and Ronald J. Williams propose the generalized delta rule, which implements a form of gradient decent on a multilayered (≥ 3) artificial neural net. The rule can be broken down into two phases where first the input is propagated forward through the net and the associated output is compared to the target value giving an error value δ_{pj}. The next phase involves feeding the error backwards through the net, where weight changes are calculated and applied. The authors then test their algorithm against different problems or with different activation functions.

Remarks

I found this paper to be a fascinating read and a great insight into the ideas in intelligent systems from 40 years ago, especially compared to how the field progressed from the original ideas pioneered by McCulloch and Pitts in 1943. Its interesting to see how much the field progressed and standardised over that time, to the point where most symbols and terms that are used in this paper are not as foreign to me as they were in the McCulloch and Pitts paper. I also appreciated the emphasis on testing their ideas and not just proselytizing them by actually showing that they can get results. I don't fault McCulloch and Pitts for not testing some of their ideas, it's not like it was easy to get your hands on a computer in '43, I just felt that these authors do a better job of being skeptical of their own work. I also liked that, for every test, they showed their data and actually made sure that their neural nets converged in a reasonable amount of time.

Overall this was one of the most interesting papers I have read in a long time and I found it surprisingly difficult to find any issues with this paper. Most of my gripes came from my own lack of understanding, which was usually minimal because the authors were good at giving detailed explanations and procedures. They never seemed to claim anything that was too far out of the scope of the paper such as how McCulloch and Pitts did, as I addressed in my last paper. I will say that I could not follow what was being done with the sigma-pi units. This section was very brief and the authors could have done a demonstration or two to emphasize some sort of usage case, but I will sum up my issues with this section to my own general lack of understanding on the topic.

As I already mentioned, I really enjoyed this paper and I can draw inspiration from many parts of it. On the paper's structure, I really appreciated that the authors included their theory with a proof, many test cases, and expanded and generalized the theory to more cases. I feel many papers lack one of these parts and I would like to structure some of my papers similarly in the future. I also found the generalization to recurrent nets fascinating as well. While they did show some examples of recurrent nets working, I would like to know if recurrent nets have been used to solve any problems that standard nets struggle with. That seems to go beyond what the paper was trying to achieve, but the fact that they even attempted to do this is very impressive.