Assignment –1

Neural Networks

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Overview:

Fifty thousand movie reviews make up the IMDb review dataset; twenty-five thousand of them are classified as "positive" or "good," and the other twenty-five thousand as "negative." Using the IMDb dataset, this study examines several methods for enhancing a neural network model's performance.

A neural network model that already exists can have several modifications applied to it, including adjustments to the activation function, loss function, units, number of hidden layers, and regularization techniques like dropout. After then, the outcomes are examined.

Data Processing:

A few preparation steps had to be taken to transform the raw text data from the IMDb reviewer dataset into a format that could be used for neural network training. Since considering every word in the dataset would provide a high-dimensional input space, we only chose the top 10,000 terms. Next, we used a dictionary to move the definitions in the top 10,000-word list to the relevant indices to transform the text reviews through integer representations.ng the integer approximations into tensors are necessary before applying neural networks. To make sure that every assessment was the same length, we reduced the length of the larger reviews and added zeros to the shorter ones. As such, each review was represented as a fixed-size vector, with each element being an index of a word.

Approaches:

We set a maximum word count and review duration for each review when the data is merged. Next, using a single 16-unit hidden layer, we constructed a simple neural network model. Adam served as the optimizer, the hidden layer parameters were dropout and hyper tuned, the triggering rates were relu and tanh, the loss parameter was binary Cross entropy, and the optimization was MSE. Next, we investigated the previously recommended strategies to improve the model's efficacy. Next, we changed the total number of hidden layers to produce prototypes with one, two, and three hidden layers that were not visible. We used the test and instruction datasets to compare, assess, and refine the models. Our results show that adding three hidden layers improved test accuracy and validity when compared to the use of only one of them.

Hidden Layers and Accuracy Percentage:

1. 1-hidden layer, 16-units Accuracy = 88.6%
2. 3-hidden layer, 16-units Accuracy = 88.4%
3. 3-hidden layer, 32-units Accuracy = 86.3%
4. 2-hidden layer, 64-units Accuracy = 86.1%
5. 3-hidden layer, 128-units Accuracy = 87.3%
6. 3-hidden layer, 16-units Accuracy = 88.1%
7. 1-hidden layer, 16-units Accuracy = 88.4%
8. 3-hidden layer, 16-units Accuracy = 88.1%
9. 2-hidden layer, 16-units Accuracy = 88.7%
10. 3-hidden layer, 16-units Accuracy = 88.1%
11. 3-hidden layer, 32-units Accuracy = 86.3%

Conclusion:

We later tried dropout regularization to prevent overfitting. By using training and test datasets, we established a novel model with dropout layers. Unlike the baseline model, our results showed that regularized dropouts reduced validation precision. As a result, it is believed that variable neural network modeling modifications have varied accuracy values and loss functions. In contrast to the Model Hyper, which had the best accuracy and loss, the three thick layers with a rate of drop-out of 0.5 may be used to provide the best results for the IMDB information set. The mean square error (MSE) loss function showed the smallest loss value when binary cross-entropy was considered. Because of the declining accuracy of the tanh activator function, disregarding the vanishing gradient problem. It has been established that building the model effectively utilizes the Adam optimized function. Because Model MSE has a tiny loss value, it is somewhat inaccurate than Model Hyper. Whenever contrasted to other models, the Model Regularization shows poor accuracy. Thus, it may be extrapolated that the Model Hyper executes the best over all the models investigated