**Assignment 2:**

**Designing and Comparing MLP Models with Word and Character Tokenization**

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**Introduction**

Multilayer Perceptrons, or MLPs, are feedforward neural networks and a great tool in the area of machine learning. They have many applications in the field, one of which will be the focus of this report. The main objective of the assignment is to modify the text preprocessing from character-level tokenization to word-level tokenization and then create an MLP model that used the word-level preprocessed IMDB dataset to train itself. Additionally, hyper-parameter optimization will be performed to experiment and find a set of best settings for the model created, followed by further testing and a comparison between a random MLP model to further show robustness.

**Methodology**

To do so however, the first step in the process was to switch the current method of tokenization to word tokenization and then train an MLP model based off the preprocessed text to compare the two methods and determine which one results in a more accurate model. This was done by simply modifying the “char\_level” parameter for the tokenizer to False, so that it would use word level tokenization on the IMDB dataset instead. Once this was done, a bag of characters and words, as well as one-hot encodings using the dataset labels were generated (one pair for training, validation, and testing). It should also be mentioned that the word-tokenization was limited to the top 10,000 most common words in the dataset as the full vocabulary was over 80,000 words.

Now that the preprocessing of the text was done, two MLP models were instanced for each of the tokenization methods used. They were each then trained individually using the same set of hyper-parameters for consistency. After training each model over three iterations, it was found that the word model performed marginally better than the character model (see experiment and results section for more details). This was mainly due to the vastly increased amount of contextualization the word model had access to, given its large vocabulary.

So now that the best model was identified, in order to attempt to gain an even greater increase in performance, hyper-parameter optimization was implemented next. The following hyper-parameters were used: learning rate, hidden layers, hidden layer sizes, batch size, optimizer, activation function. Moving forward, the process of implementing hyper-parameter optimization was relatively straight-forward. First, a range of possible values were assigned to each parameter, such as a model being able to have one, two, or three hidden layers or using Adam, SGD, or RMSprop optimizer during backward propagation. Then, a sequence of 50 runs were carried out, each run choosing a unique subset combination of hyper-parameters randomly to ensure parameters changed with each iteration. During each iteration, the model would be trained at least three times, and then finally tested against the test dataset to obtain some performance metrics such as accuracy and loss. Lastly, once all 50 runs were complete, the set of hyper-parameters that resulted in the highest accuracy was chosen as the best overall (see experiment and results section). The reason why accuracy was chosen as the performance metric is because for well-balanced datasets such as the IMDB dataset being used, accuracy is a good metric for judging the performance of a model trained using it.

The last experiments conducted were to prove the robustness of the model using the best hyper-parameters found. This was done by running a comparison between the current MLP model against the random MLP provided, to see which one would have better accuracy overall and lower standard error. Each model was given the best hyper-parameters, and then ran through five unique runs, involving three iterations of training each. Once the accuracies were collected across all five tests for each model, the mean accuracy and standard error were calculated.

**Experiment and Results**

This section displays all the results collected throughout the experiments performed during the assignment. Additional data on performance metrics during training and such can be found in the Jupyter Notebook provided with the report. The first major experiement performed was the comparison between character and word tokenization when it came to preprocessing the IMDB dataset. The results below show that word tokenization did perform better as it has a greater level of accuracy while also having a loss closer to zero.

|  |  |  |
| --- | --- | --- |
| **Character Vs. Word Tokenization** | | |
|  | **Character Tokenization** | **Word Tokenization** |
| **Test Accuracy** | 0.6004 | 0.8670 |
| **Test Loss** | 0.6656 | 0.3572 |

The next set of results shown below are the 50 tests carried out of different sets of hyper-parameters. Each row represents an individual run, with the hyper-parameters that were used and the resulting accuracy obtained after using the trained MLP model against the test dataset.

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Run** | **Learning Rate** | **Hidden Layers** | **Hidden Size** | **Batch Size** | **Optimizer** | **Activation Function** | **Test Accuracy** |
| **1** | 0.0005 | 3 | 256 | 32 | Adam | ReLU | **0.8595** |
| **2** | 0.0001 | 1 | 128 | 128 | SGD | ReLU | **0.5290** |
| **3** | 0.001 | 3 | 512 | 64 | Adam | Leaky ReLU | **0.8495** |
| **4** | 0.0001 | 1 | 512 | 128 | Adam | Tanh | **0.8640** |
| **5** | 0.0001 | 1 | 512 | 64 | SGD | Tanh | **0.5216** |
| **6** | 0.0005 | 1 | 512 | 32 | SGD | Leaky ReLU | **0.6331** |
| **7** | 0.0001 | 1 | 512 | 32 | Adam | Tanh | **0.8756** |
| **8** | 0.001 | 3 | 256 | 128 | SGD | ReLU | **0.5806** |
| **9** | 0.001 | 1 | 512 | 64 | Adam | ReLU | **0.8830** |
| **10** | 0.0001 | 1 | 128 | 32 | SGD | ReLU | **0.5116** |
| **11** | 0.0001 | 1 | 512 | 64 | SGD | ReLU | **0.5031** |
| **12** | 0.0005 | 2 | 512 | 32 | Adam | Tanh | **0.8670** |
| **13** | 0.0010 | 2 | 128 | 64 | Adam | Leaky ReLU | **0.8826** |
| **14** | 0.0005 | 2 | 256 | 64 | RMSprop | Tanh | **0.8750** |
| **15** | 0.0005 | 1 | 256 | 128 | Adam | Tanh | **0.8852** |
| **16** | 0.0001 | 3 | 256 | 64 | SGD | ReLU | **0.5190** |
| **17** | 0.001 | 2 | 256 | 32 | RMSprop | ReLU | **0.8577** |
| **18** | 0.0005 | 2 | 512 | 64 | RMSprop | ReLU | **0.8596** |
| **19** | 0.0005 | 1 | 512 | 128 | Adam | Leaky ReLU | **0.8809** |
| **20** | 0.0005 | 1 | 512 | 64 | SGD | Leaky ReLU | **0.5610** |
| **21** | 0.001 | 1 | 256 | 32 | Adam | Tanh | **0.8856** |
| **22** | 0.001 | 1 | 512 | 32 | RMSprop | Tanh | **0.8674** |
| **23** | 0.0005 | 2 | 128 | 128 | SGD | ReLU | **0.5446** |
| **24** | 0.0001 | 2 | 128 | 32 | SGD | ReLU | **0.5612** |
| **25** | 0.0001 | 2 | 512 | 32 | SGD | ReLU | **0.5736** |
| **26** | 0.0001 | 3 | 256 | 32 | RMSprop | ReLU | **0.8546** |
| **27** | 0.0005 | 1 | 256 | 128 | Adam | Tanh | **0.8833** |
| **28** | 0.0001 | 2 | 256 | 32 | Adam | ReLU | **0.8547** |
| **29** | 0.0001 | 1 | 128 | 128 | Adam | Leaky ReLU | **0.8262** |
| **30** | 0.0005 | 1 | 128 | 128 | RMSprop | ReLU | **0.8722** |
| **31** | 0.0001 | 1 | 128 | 32 | Adam | Tanh | **0.8645** |
| **32** | 0.0005 | 3 | 256 | 32 | RMSprop | Tanh | **0.8734** |
| **33** | 0.0005 | 3 | 512 | 64 | SGD | Tanh | **0.5909** |
| **34** | 0.0001 | 3 | 128 | 128 | Adam | Tanh | **0.8377** |
| **35** | 0.0005 | 2 | 256 | 128 | SGD | Leaky ReLU | **0.5394** |
| **36** | 0.0010 | 3 | 256 | 64 | Adam | Tanh | **0.8787** |
| **37** | 0.0001 | 3 | 256 | 32 | SGD | Tanh | **0.5255** |
| **38** | 0.001 | 2 | 128 | 64 | SGD | ReLU | **0.5392** |
| **39** | 0.001 | 2 | 256 | 64 | SGD | Leaky ReLU | **0.6144** |
| **40** | 0.0005 | 1 | 256 | 128 | SGD | ReLU | **0.5099** |
| **41** | 0.0005 | 3 | 256 | 128 | RMSprop | Tanh | **0.8717** |
| **42** | 0.001 | 1 | 512 | 128 | SGD | Leaky ReLU | **0.5606** |
| **43** | 0.0005 | 3 | 128 | 128 | SGD | Leaky ReLU | **0.4878** |
| **44** | 0.001 | 1 | 256 | 64 | Adam | ReLU | **0.8780** |
| **45** | 0.0001 | 2 | 256 | 64 | SGD | Leaky ReLU | **0.5106** |
| **46** | 0.0001 | 3 | 256 | 128 | SGD | Leaky ReLU | **0.5192** |
| **47** | 0.001 | 3 | 512 | 64 | Adam | Leaky ReLU | **0.8603** |
| **48** | 0.0001 | 3 | 128 | 64 | RMSprop | Tanh | **0.8642** |
| **49** | 0.0005 | 2 | 256 | 32 | RMSprop | Leaky ReLU | **0.8770** |
| **50** | 0.0001 | 3 | 128 | 32 | SGD | Tanh | **0.4906** |

Based on the runs carried out above, the set of hyper-parameters shown resulted in the best performance. As mentioned previously, this is determined by accuracy, since that is a good metric to use given that the IMDB dataset is being used.

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Best Model Found** | | | | | | | |
| **Run** | **Learning Rate** | **Hidden Layers** | **Hidden Size** | **Batch Size** | **Optimizer** | **Activation Function** | **Test Accuracy** |
| **21** | 0.001 | 1 | 256 | 32 | Adam | Tanh | **0.8856** |

After identifying the best set of hyper-parameters, a test for additional robustness of the model was performed. The current MLP model was put through more iterations of training and testing. Then, a random MLP model with the same hyper-parameters was used and put through the same iterations of training. The following table below is a summary of the overall average accuracy and standard error for the two models based on the best hyper-parameters found:

|  |  |  |
| --- | --- | --- |
| **MLP Model Vs. Random MLP Model Comparison** | | |
|  | **Mean Test Accuracy** | **Standard Error** |
| **MLP Model** | 0.8849 | 0.0008 |
| **Random MLP Model** | 0.7201 | 0.0008 |

Once the final robustness experiment was done, this concluded the experimental portion of the assignment as results could now be drawn.

**Discussion**

**Conclusion**

* **Introduction:** Objectives and overview of the work.
* **Methodology:** Detailed explanation of tokenization changes and hyper-parameter optimization strategy.
* **Experiments and Results:**
  + Comparison between character-level and word-level tokenization.
  + Tables/graphs for hyper-parameter experiments.
  + Final model performance with mean accuracy and standard error.
* **Discussion:** Analysis of results, challenges encountered, and insights.
* **Conclusion:** Summarize the key findings.