Journal of Harbin Engineering University
ISSN: 1006-7043
Vol 45 No. 4
April 2024

A Study of the Accuracy of the Model Sequential in Deep Learning: Focusing on a Survey

Namkil Kang
Professor
College of Liberal ArtsFar East University
South Korea

Abstract - The ultimate goal of this paper is to provide an in-depth analysis of the accuracy of the model sequential in deep learning. A point to note is that the sequential model worked properly for train data and validation data and that this took place after epoch 4. When learning took place once, the accuracy rate of the model sequential was considerably low, whereas learning happened twice, that of the model sequential improved dramaticaly. A further point to note is that after epoch 5, train data and validation data were perfectly predicted by the sequential model. A major point of this paper is that the val_accuracy of the sequential model reached a peak from the beggining to the end, whereas the accuracy of the sequential model increased dramatically to 100% after epoch 3. It is worthwhile pointing out that the sequential model judged cold patients as cold patients, whereas it judged no cold patients as no cold patients. This in turn indicates that test data were perfectly predicted by the sequential model. It must be stressed, on the other hand, that the proportion of the so-called recall is 100%. Put differently, our model judged true as true. It therefore seems reasonable to conclude that test data were also perfectly predicted by the sequential model, hence indicating that the sequential model counts as a good model.
Keywords: deep learning, hidden layer, optimizer, accuracy, recall, precision

1. **Introduction**

The main purpose of this paper is to provide the accuracy rate of the model sequential in deep learning. I conducted a survey about whether my students had a cold or not for recent six months. I asked 73 students about their symptoms. I classified a cold patient into 1, while I classified no patient into 0. In this paper, I trained the model sequential to predict whether or not each student was a cold patient. I divided data into train data (80%) and test data (20%). In addition, I used 25% of train data as validation data. I attempted to prenormalize data by using minmaxscaler. It is important to note that we used three hidden layers to improve the accuracy from the sequential model. In each layer, the number of nodes is 48, 24, and 12, respectively. Also, we used relu and softmax as activation. First, we trained the model sequential to predict whether or not each student had a cold. When it comes to epoch, learning took place 25 times in order to improve the accuracy of the sequential model. Second, we provided the loss, accuracy, val_loss, and val_accuracy of the model sequential. Third, we provided the accuracy rate of test data along with that of train data. Finally, we attempted to provide the relevant classification report through which we can see how the sequential model worked for test data.

2. **Methods**

The main goal of this paper is to make the model sequential predict whether each student had a cold or not. For this goal, python was used. In order to provide the relevant data (train data, validation data, and test data), we conducted a survey about whether each student had a cold or not. 73 students participated in my survey. They are attending my classes (Business English, Global English 1, and Global English 3: 3 credits each). I asked them about their symptoms to examine whether they had a cold or not for recent six months. After finishing the survey, I classified a cold patient into 1, whereas I classified no cold patient into 0. In addition to this, in order to prenormalize the relevant data, we used minmaxscaler. Also, we used three hidden layers to improve the accuracy rate of the model sequential and the number of nodes were 48, 24, and 12, respectively. As activation, we used relu and softmax. The so-called activation plays a role in regulating weight and bias. As optimizer, we used adam. The so-called optimizer refers to the function of finding the answer, going backward. Note that our learning rate is 0.07.

3. Results

3.1 Epoch

This section focuses on probing into the loss, val_loss, accuracy, and val_accuracy of the model sequential by using the so-called epoch. The term epoch refers to the number of learning. In this paper, learning took place 25 times to improve the accuracy of the model sequential. Take a look at the following table:

Table 1 Epoch

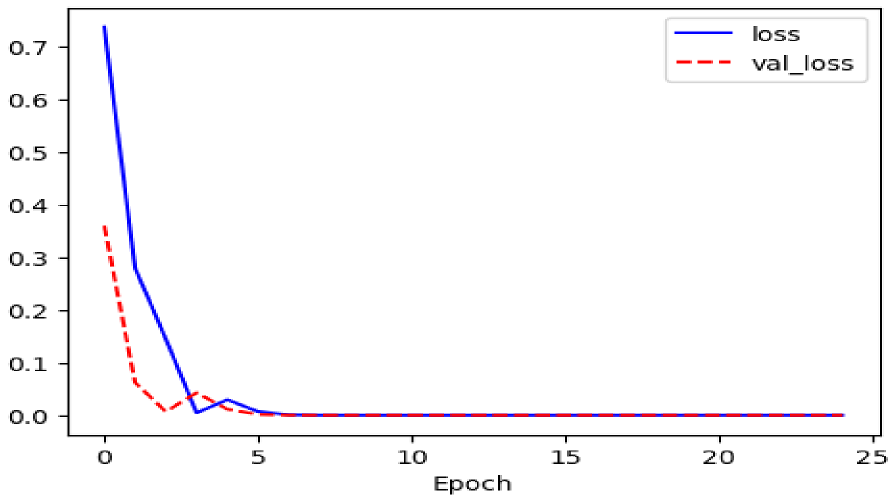
The Number of Epoch	**Loss**	**Accuracy**	**Val_loss**	**Val_accurracy**
Epoch 1	0.7373	0.2093	0.3598	1.0000
Epoch 2	0.2798	0.9767	0.0622	1.0000
Epoch 3	0.1449	0.9767	0.0067	1.0000
Epoch 4	0.0044	1.0000	0.0426	1.0000
Epoch 5	0.0294	1.0000	0.0114	1.0000
Epoch 6	0.0070	1.0000	0.0014	1.0000
Epoch 7	8.3804e-04	1.0000	1.6299e-04	1.0000
Epoch 8	6.7993e-05	1.0000	2.2887e-05	1.0000
Epoch 9	1.4980e-05	1.0000	4.1484e-06	1.0000
Epoch 10	2.9608e-06	1.0000	9.6957e-07	1.0000
Epoch 11	6.5981e-07	1.0000	2.7815e-07	1.0000
Epoch 12	3.7703e-07	1.0000	8.7420e-08	1.0000
Epoch 13	3.1327e-07	1.0000	2.3842e-08	1.0000
Epoch 14	4.0198e-07	1.0000	1.5895e-08	1.0000
Epoch 15	4.4357e-07	1.0000	7.9473e-09	1.0000
Epoch 16	5.4614e-07	1.0000	0.0000e+00	1.0000
Epoch 17	6.5980e-07	1.0000	0.0000e+00	1.0000
Epoch 18	7.7901e-07	1.0000	0.0000e+00	1.0000
Epoch 19	8.9267e-07	1.0000	0.0000e+00	1.0000
Epoch 20	9.9524e-07	1.0000	0.0000e+00	1.0000
Epoch 21	1.0784e-06	1.0000	0.0000e+00	1.0000
Epoch 22	1.1699e-06	1.0000	0.0000e+00	1.0000
Epoch 23	1.1727e-06	1.0000	0.0000e+00	1.0000
Epoch 24	1.1643e-06	1.0000	0.0000e+00	1.0000
Epoch 25	1.1422e-06	1.0000	0.0000e+00	1.0000

To begin with, let us define terms used in Table 1. The term loss refers to the difference between the actual value (the answer) and the predictive value. The smaller the difference between the actual value and the predictive value is, the better the relevant model is. The term val_loss refers to the loss value of validation data. More specifically, it refers to the difference between the actual value and the predictive value of validation data. The so-called validation data is the part of train data. For validation data, we used 25 percent of train data. The term val_accuracy refers to the accuracy of validation data. On the other hand, the term accuracy refers to the accuracy of train data. It is worthwhile pointing out that when epoch was 1, the accuracy rate of the model sequential was 20.93%. This in turn indicates that when learning took place once, the accuracy rate of the model sequential was considerably low, hence indicating that this model did not work properly. What is interesting is that its loss was 73.73%, thus indicating that this is not a good model. Note, however, that when epoch was 2, things were getting better. Put differently, the accuracy rate of the model sequential was getting better when learning took place twice. More specifically, the accuracy rate of the model sequential was 97.67% when learning happened twice. Perhaps it is worthwhile noting that the accuracy rate of validation data was 100%. This seems to suggest that the model sequential worked properly for validation data. Notice, however, that for validation data, we used 25 percent of train data. This may imply that data were well predicted by the model sequential since small data as validation data were used. It is particularly noteworthy that the same can be said of epoch 3. When epoch was 2 and 3, the accuracy rate of the model sequential was 97.67%. Even though learning took place three times, the accuracy of the model sequential did not improve. Note, however, that when epoch was 3, the loss of the model sequential decreased. On the other hand, val_accuracy was 100%. From the beginning, val_accuracy was 100% and did not decrease. Quite interestingly, val_loss continued to decrease whenever epoch was changed. It is important to note that when epoch was 4, the accuracy rate of the sequential model reached a peak (100%). It is significant to note that after epoch 4, the accuracy rate of the sequential model continued to show the same pattern. Put differently, train data were well predicted by the sequential model (100%). It is worth noting that the loss of the sequential model decreased to 0.4% when epoch was 4. Particularly noteworthy is that in the case of validation data, the accuracy rate of the sequential model continued to exhibit the same property (100%) from epoch 1 to epoch 25. It is important to mention that the loss of the sequential model decreased to 0.000 after epoch 8. This in turn suggests that train data were well predicted by the model sequential. Exactly the same can be said about validation data. That val_accuracy was 100% in turn suggests that the sequential model worked well for validation data and that it is a good model. We thus conclude that the sequential model worked properly for train data and validation data and that this took place after epoch 4.

3.2 The Loss, Val_loss, and Accuracy of the Model Sequential

This section is devoted to going over the loss, val_loss, and accuracy of the model sequential. We provide the relevant graph, which in turn shows how the model sequential worked well with respect to train data and validation data. Also, we probe into the accuracy of the model sequential with respect to test data. Figure 1 shows how the sequential model worked with respect to train data and validation data. The blue line refers to the loss of the sequential model, whereas the red dotted line refers to the val_loss of validation data:

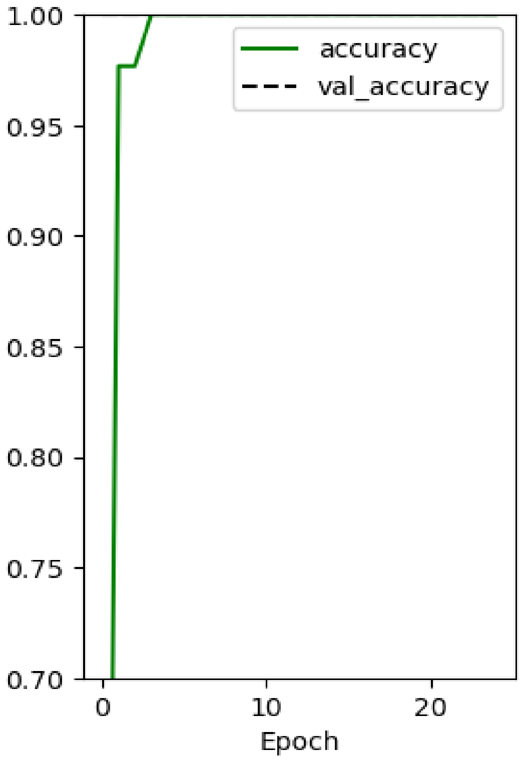
Figure 1 The Loss and Val_loss of the Model Sequential



Perhaps it is worthwhile saying that when epoch was 1, the loss of the sequential model was considerably high. More specifically, the figure (the loss of the sequential model) increased to 0.7 (more than 70%). This in turn implies that the model sequential did not work properly for train data. It must be stressed, on the other hand, that when epoch was 1, the val_loss of the sequential model was also considerably high. The figure increased to more than 35%. This in turn suggests that the model sequential did not work well for validation data. We used 25% of train data as validation data. As can be seen from the graph, there was a gradual decline in the val_loss of the sequential model. This in turn shows that whenever learning took place, there was a steady fall in the val_loss of the sequential model. Note that we used 3 hidden layers in order to improve the accuracy rate of the model sequential. In fact, when epoch was 2, there was a dramatic decline in the val_loss of the sequential model. After this, the val_loss of the sequential model continued to stay within 0. This in turn indicates that the model sequential worked well for validation data. What is interesting is that after epoch 5, the val_loss of the sequential model was within 0. What this suggests is that there is no difference between the actual value (the answer) and the predictive value of validation data. It should be noted, on the other hand, that when epoch was 3, there was a sharp fall in the loss of the sequential model. More specifically, the figure (the loss of the sequential model) decreased to 0, which in turn shows that there is no difference between the actual value (the answer) and the predictive value of train data. Notice, however, that there was a slight increase in the loss of the sequential model. After this, the figure (the loss of the sequential model) continued to stay within 0. This in turn indicates that there is no difference between the actual value and the predictive value in train data. Moreover, this in turn implies that the model sequential continued to work properly for train data. We thus conclude that after epoch 5, train data and validation data were well predicted by the sequential model.

Now attention is paid to the accuracy and val_accuracy of train data and validation data. Figure 2 shows the accuracy and val_accuracy of the model sequential:

Figure 2 The Accuracy and Val_accuracy of the Sequential Model



It is worth mentioning that when epoch was 1, the accuracy rate of the sequential model was about 96%. The term accuracy refers to the accuracy rate of train data. It must be stressed that when epoch was 2, the accuracy rate of the sequential model was not changed. Simply put, the accuracy rate of the sequential model stayed within about 96%. It is worth noticing that when epoch was more than 3, there was a steady increase in the accuracy of the model sequential. To go into detail, the figure (the accuracy of the sequential model) increased to 100%. After this, the accuracy rate of the sequential model continued to stay within 100%. That is to say, the accuracy of the sequential model showed the stable pattern. This amounts to saying that train data were well predicted by the sequential model when epoch was more than 3. It is also appropriate to mention that the val_accuracy of the sequential model (the green dotted line) cannot be seen from the graph. This in turn means that the accuracy of the sequential model continued to stay within 100% from epoch 1 to epoch 25. That is why the green dotted line disappeared from the graph. What this suggests is that the model sequential worked well for validation data from the beggining to the end. We thus conclude that the val_accuracy of the sequential model reached a peak from the beggining to the end, whereas the accuracy of the sequential model increased dramatically to 100% after epoch 3.

Now attention is paid to test data. The split proportion of train data and test data in our experiment is 80/20. That is to say, we used 20 percent of train data as test data. Most importantly, the accuracy rate of test data was 100%. This in turn indicates that our model worked well for test data, hence indicating a good model. It would be unfair not to note that the loss of the sequential model is 0.000. This in turn indicates that there is no difference between the actual value (the answer) and the predictive value.

3.3. The Classification Report

In what follows, we aim at providing the classification report of test data. In Table 2, 0 indicates no patient, while 1 indicates a cold patient. The term support indicates the number of test data. The term accuracy means that our model judges true as true and it judges false as false. The term recall means that our model judges true as true. On the other hand, the term precision refers to the proportion of truth in what our model judges as true.

Table 2 Classification Report (Test Data)

	Precision	**Recall**	**F1-score**	**Support**
0	1.00	1.00	1.00	7
1	1.00	1.00	1.00	8
Accuracy			1.00	15
Macro Avg	1.00	1.00	1.00	15
Weighted Avg	1.00	1.00	1.00	15

As can be seen from Table 2, the number of cold patients is 8, whereas that of no patients is 7. As exemplified in Table 2, the sequential model judged true as true, while it judged false as false. Simply put, its accuracy rate is 100%. This in turn indicates that the sequential model worked well for test data. We take it as indicating that 15 test sets were perfectly predicted by the sequential model. It must be noted, on the other hand, that the proportion of the so-called recall is 100%. Put differently, our model judged true as true. It must be emphasized that the proportion of truth in what our model judged as true is also 100%. That is to say, the proportion of the so-called precision is 100%. It therefore seems reasonable to assume that test data (15 test sets) were perfectly predicted by the sequential model, thus implying that the sequential model counts as a good model. For the analysis of big data, machine learning, and deep learning, see Kang (2024a, 2024b, 2024c, 2024d, 2024e, 2024f).

4. Conclusion

To sum up, we have provided the accuracy of the model sequential in deep learning. In section 3.1, we have contended that the sequential model worked properly for train data and validation data and that this took place after epoch 4. When learning took place once, the accuracy rate of the model sequential was considerably low, whereas learning happened twice, that of the model sequential improved dramaticaly. In section 3.2, we have argued that after epoch 5, train data and validation data were perfectly predicted by the sequential model. We have further argued that the val_accuracy of the sequential model reached a peak from the beggining to the end, whereas the accuracy of the sequential model increased dramatically to 100% after epoch 3. In section 3.3, we have maintained that the sequential model judged cold patients as cold patients, while it judged no cold patients as no cold patients. Simply put, its accuracy rate is 100%. This in turn indicates that the sequential model worked well for test data. It must be noted, on the other hand, that the proportion of the so-called recall is 100%. Put differently, our model judged true as true. It therefore seems reasonable to conclude that test data (15 test sets) were perfectly predicted by the sequential model, thus implying that the sequential model counts as a good model.

References

[1] Kang, N (2024a). A Big Data Analysis of a Hot Political Issue. *Studies in Linguistics* 70, 149-165

[2] Kang, N (2024b). The Ukrine War in BBC News: A Big Data Analysis. *International Journal of Applied Engineering and Technology* 6(1), 1548-1555

[3] Kang, N (2024c). A Study of the Prediction of the Model Logistic Regression in Machine Learning: Focusing on a Survey. *Semiconductor Optoelectonics* 43(1), 86-94

[4] Kang, N (2024d). The Spring of Seoul: A Big Data Analysis. *Semiconductor Optoelectonics* 43(1), 264-272

[5] Kang, N (2024e). A Study of the Prediction of the Three Models Logistic Regression, Gaussian Naive Bayes, and Multi-Layer Perceptron Classifier in Machine Learning. *Semiconductor Optoelectonics* 43(1), 253-263

[6] Kang, N (2024f). An Analysis of the Prediction Power of Four Models in Machine Learning and Deep Learning: Focusing on the Reviews of the Movie Noryang. *A Jungang Journal of English Language and Literature* 66(1), 101-122

Appendix

Number	cough	fever	runny nose	sore throat	headache	back pain	cold
1	0	0	0	0	0	1	0
2	0	0	1	0	0	0	1
3	0	1	1	1	0	1	1
4	0	0	0	0	0	1	0
5	1	1	0	1	0	0	1
6	1	0	0	1	0	0	1
7	1	0	1	0	0	1	1
8	0	0	0	0	1	1	0
9	0	0	0	0	0	1	0
10	0	1	1	1	0	0	1
11	0	0	0	0	1	1	0
12	0	0	0	0	1	1	0
13	0	0	0	0	1	1	0
14	0	0	0	0	1	1	0
15	0	0	0	0	0	1	0
16	0	1	1	1	0	0	1
17	0	1	1	1	0	1	1
18	0	0	1	1	0	1	1
19	0	0	1	0	0	0	1
20	1	0	0	1	0	0	1

21	1	0	1	0	0	0	1
22	1	0	0	1	0	0	1
23	0	0	0	0	0	1	0
24	0	0	0	0	0	1	0
25	1	1	1	1	1	1	1
26	1	1	1	0	0	0	1
27	0	0	0	1	0	0	1
28	0	0	0	0	0	1	0
29	0	0	0	0	0	1	0
30	1	1	1	1	0	0	1
31	0	0	0	0	1	1	0
32	0	0	0	0	0	1	0
33	1	1	1	0	0	0	1
34	0	0	0	0	0	1	0
35	0	1	1	1	0	0	1
36	0	0	0	0	0	1	0
37	0	0	0	1	1	1	1
38	0	1	1	1	0	0	1
39	0	0	0	0	0	1	0
40	0	0	0	0	0	1	0
41	1	1	1	1	0	0	1
42	1	1	1	1	0	0	1
43	0	0	0	0	1	1	0
44	1	1	1	1	0	0	1
45	0	0	0	0	1	1	0
46	0	1	1	1	0	0	1
47	0	0	0	0	1	0	0
48	0	0	1	1	0	0	1
49	1	1	1	1	0	0	1
50	0	0	0	0	1	1	0
51	0	1	1	1	0	0	1
52	0	0	0	0	0	1	0
53	0	0	0	0	0	1	0
54	0	0	0	0	0	1	0
55	0	0	0	0	0	1	0
56	1	1	0	0	0	0	1
57	0	0	0	0	0	1	0
58	0	0	0	0	0	1	0
59	0	0	1	0	0	0	1
60	1	1	1	0	0	0	1

61	1	1	1	0	0	0	1
62	0	0	0	0	0	1	0
63	1	1	1	0	0	0	1
64	1	1	1	1	0	0	1
65	1	1	1	0	0	0	1
66	0	0	0	0	1	1	0
67	0	1	1	0	0	0	1
68	0	0	0	0	1	1	0
69	1	1	1	0	0	0	1
70	0	1	1	0	0	0	1
71	0	0	0	0	0	1	0
72	1	1	1	0	0	0	1
73	0	0	0	0	0	1	0