Advanced Machine Learning

Assignment 1: Neural Networks

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```
%%capture
In [113...
           # Installing required packages
           !pip install tensorflow
           !pip install tensorflow-datasets
          (imdb_a_train, imdb_b_train), (imdb_a_test, imdb_b_test) = imdb.load_data(num_words=100)
In [114...
          # Importing required Libraries
In [115...
          import numpy as np
          from tensorflow.keras.datasets import imdb
           from tensorflow.keras.models import Sequential
           from tensorflow.keras.layers import Dense, Dropout
          max([max(sequence) for sequence in imdb a train])
In [116...
          9999
Out[116]:
In [117...
          # Preparing the data for the model
           # Retrieving a dictionary mapping words to their index in the IMDB dataset
          word_index = imdb.get_word_index()
          # Creating a reverse dictionary and mapping the indices back to the original words
          reverse_word_index = dict(
               [(value, key) for (key, value) in word_index.items()])
          # Create models with different configurations
          # Decoding reviews from the IMDB dataset
           decoded_review = " ".join([reverse_word_index.get(i - 3, "?") for i in imdb_a_train[0]
          # Encoding the integer sequences via multi-hot encoding
In [118...
          import numpy as np
          def vectorize sequences(sequences, dimension=10000):
               results = np.zeros((len(sequences), dimension))
               for i, sequence in enumerate(sequences):
                   for j in sequence:
                       results[i, j] = 1.
               return results
           imdb_train = vectorize_sequences(imdb_a_train)
           imdb_test = vectorize_sequences(imdb_a_test)
          imdb train[0]
In [119...
```

```
Out[119]: array([0., 1., 1., ..., 0., 0., 0.])
           value train = np.asarray(imdb b train).astype("float32")
In [120...
           value_test = np.asarray(imdb_b_test).astype("float32")
           # Create models with different configurations
In [121...
           # One hidden layer and 32 hidden units using Tanh activation function instead of relu
           model_one_hidden_layer = Sequential()
           model_one_hidden_layer.add(Dense(32, activation='tanh'))
           model_one_hidden_layer.add(Dense(1, activation='sigmoid'))
          # Compiling model using MSE
In [122...
           model_one_hidden_layer.compile(optimizer='adam', loss='mean_squared_error', metrics=['
          # Validation
In [123...
           a val = imdb train[:10000]
           partial_a_train = imdb_train[10000:]
           b_val = value_train[:10000]
           partial_b_train = value_train[10000:]
          # Training the model with validation set
In [124...
           history_one_hidden_layer = model_one_hidden_layer.fit(partial_a_train,
                                                                  partial_b_train,
                                                                  epochs=20,
                                                                  batch size=512,
                                                                  validation_data=(a_val,b_val))
```

```
Epoch 1/20
30/30 [=============== ] - 3s 43ms/step - loss: 0.1534 - accuracy: 0.80
93 - val loss: 0.1060 - val accuracy: 0.8742
Epoch 2/20
30/30 [================= ] - 0s 14ms/step - loss: 0.0769 - accuracy: 0.91
63 - val loss: 0.0891 - val accuracy: 0.8898
Epoch 3/20
30/30 [============ ] - 0s 13ms/step - loss: 0.0560 - accuracy: 0.94
23 - val loss: 0.0854 - val accuracy: 0.8893
Epoch 4/20
30/30 [=============== ] - 0s 13ms/step - loss: 0.0436 - accuracy: 0.96
01 - val_loss: 0.0841 - val_accuracy: 0.8869
Epoch 5/20
30/30 [============== ] - 0s 13ms/step - loss: 0.0349 - accuracy: 0.97
07 - val loss: 0.0855 - val accuracy: 0.8848
Epoch 6/20
30/30 [============== ] - 0s 13ms/step - loss: 0.0283 - accuracy: 0.97
82 - val_loss: 0.0863 - val_accuracy: 0.8811
Epoch 7/20
30/30 [============== ] - 0s 13ms/step - loss: 0.0236 - accuracy: 0.98
33 - val loss: 0.0876 - val accuracy: 0.8795
30/30 [================ ] - 0s 13ms/step - loss: 0.0199 - accuracy: 0.98
77 - val loss: 0.0896 - val accuracy: 0.8790
Epoch 9/20
30/30 [============== ] - 0s 13ms/step - loss: 0.0168 - accuracy: 0.98
99 - val loss: 0.0915 - val accuracy: 0.8756
Epoch 10/20
30/30 [============== ] - 0s 13ms/step - loss: 0.0140 - accuracy: 0.99
24 - val loss: 0.0928 - val accuracy: 0.8764
Epoch 11/20
30/30 [============== ] - 0s 14ms/step - loss: 0.0120 - accuracy: 0.99
38 - val_loss: 0.0943 - val_accuracy: 0.8737
Epoch 12/20
30/30 [============== ] - 0s 17ms/step - loss: 0.0103 - accuracy: 0.99
45 - val_loss: 0.0960 - val_accuracy: 0.8721
Epoch 13/20
30/30 [============== ] - 1s 17ms/step - loss: 0.0089 - accuracy: 0.99
53 - val loss: 0.0973 - val accuracy: 0.8716
Epoch 14/20
30/30 [============== ] - 1s 18ms/step - loss: 0.0079 - accuracy: 0.99
59 - val_loss: 0.0988 - val_accuracy: 0.8705
Epoch 15/20
30/30 [============== ] - 1s 18ms/step - loss: 0.0071 - accuracy: 0.99
63 - val_loss: 0.1004 - val_accuracy: 0.8680
Epoch 16/20
30/30 [============== ] - 1s 17ms/step - loss: 0.0064 - accuracy: 0.99
65 - val loss: 0.1007 - val accuracy: 0.8689
Epoch 17/20
30/30 [============== ] - 1s 17ms/step - loss: 0.0058 - accuracy: 0.99
67 - val_loss: 0.1018 - val_accuracy: 0.8678
Epoch 18/20
30/30 [============== ] - 1s 18ms/step - loss: 0.0053 - accuracy: 0.99
69 - val loss: 0.1028 - val accuracy: 0.8665
Epoch 19/20
30/30 [============== ] - 1s 19ms/step - loss: 0.0049 - accuracy: 0.99
70 - val_loss: 0.1039 - val_accuracy: 0.8654
Epoch 20/20
30/30 [============== ] - 1s 17ms/step - loss: 0.0046 - accuracy: 0.99
71 - val_loss: 0.1044 - val_accuracy: 0.8660
```

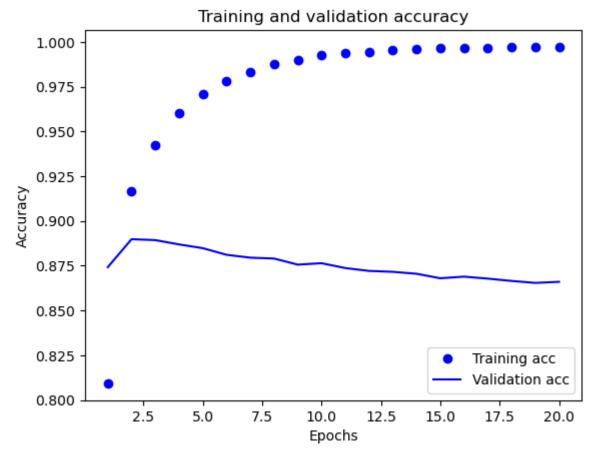
```
In [125...
           history_dict = history_one_hidden_layer.history
           history_dict.keys()
           dict_keys(['loss', 'accuracy', 'val_loss', 'val_accuracy'])
Out[125]:
In [126...
           # Plotting the training and validation loss
           import matplotlib.pyplot as plt
           history_dict = history_one_hidden_layer.history
            loss_values = history_dict["loss"]
           val_loss_values = history_dict["val_loss"]
           epochs = range(1, len(loss values) + 1)
           plt.plot(epochs, loss_values, "bo", label="Training loss")
plt.plot(epochs, val_loss_values, "b", label="Validation loss")
           plt.title("Training and validation loss")
           plt.xlabel("Epochs")
           plt.ylabel("Loss")
           plt.legend()
           plt.show()
```

Training and validation loss 0.16 Training loss Validation loss 0.14 0.12 0.10 0.08 0.06 0.04 0.02 0.00 2.5 5.0 7.5 10.0 12.5 15.0 17.5 20.0 Epochs

```
In [127... # Plotting the training and validation accuracy

plt.clf()
    acc = history_dict["accuracy"]
    val_acc = history_dict["val_accuracy"]
    plt.plot(epochs, acc, "bo", label="Training acc")
    plt.plot(epochs, val_acc, "b", label="Validation acc")
    plt.title("Training and validation accuracy")
    plt.xlabel("Epochs")
    plt.ylabel("Accuracy")
```

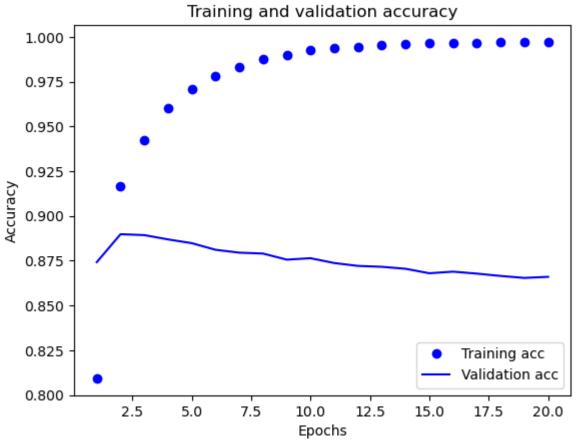
```
plt.legend()
plt.show()
```



```
results = model_one_hidden_layer.evaluate(imdb_test,value_test)
In [128...
         554
         # Adding Dropout Layer & Regulaizers
In [129...
         from tensorflow import keras
         from tensorflow.keras import layers
         from keras.layers import Dense
         from tensorflow.keras import regularizers
         from keras.layers import Dropout
         model_one_hidden_layer = Sequential()
         model one hidden layer.add(Dense(32, activation='tanh', activity regularizer=regulariz
         model_one_hidden_layer.add(Dropout(0.5))
         model one hidden layer.add(Dense(1, activation='sigmoid'))
         # compiling the model
         model_one_hidden_layer.compile(optimizer="adam",
                                    loss="mean_squared_error",
                                    metrics=["accuracy"])
         # Validating the model
         a_val = imdb_train[:10000]
```

```
Epoch 1/20
30/30 [=============== ] - 2s 47ms/step - loss: 0.1853 - accuracy: 0.77
97 - val loss: 0.1419 - val accuracy: 0.8633
Epoch 2/20
30/30 [================= ] - 0s 15ms/step - loss: 0.1202 - accuracy: 0.90
12 - val loss: 0.1214 - val accuracy: 0.8882
Epoch 3/20
30/30 [============== ] - 0s 17ms/step - loss: 0.0999 - accuracy: 0.93
16 - val loss: 0.1153 - val accuracy: 0.8889
Epoch 4/20
30/30 [============== ] - 1s 18ms/step - loss: 0.0866 - accuracy: 0.94
89 - val_loss: 0.1128 - val_accuracy: 0.8869
Epoch 5/20
30/30 [============== ] - 1s 17ms/step - loss: 0.0772 - accuracy: 0.96
01 - val loss: 0.1124 - val accuracy: 0.8825
Epoch 6/20
30/30 [=============== ] - 1s 17ms/step - loss: 0.0699 - accuracy: 0.96
83 - val_loss: 0.1137 - val_accuracy: 0.8772
Epoch 7/20
30/30 [============== ] - 1s 19ms/step - loss: 0.0644 - accuracy: 0.97
52 - val loss: 0.1156 - val accuracy: 0.8739
30/30 [================ ] - 1s 19ms/step - loss: 0.0596 - accuracy: 0.97
87 - val loss: 0.1163 - val accuracy: 0.8737
Epoch 9/20
30/30 [============== ] - 1s 23ms/step - loss: 0.0553 - accuracy: 0.98
31 - val loss: 0.1187 - val accuracy: 0.8682
Epoch 10/20
30/30 [============== ] - 1s 19ms/step - loss: 0.0515 - accuracy: 0.98
67 - val loss: 0.1202 - val accuracy: 0.8657
Epoch 11/20
30/30 [============== ] - 1s 20ms/step - loss: 0.0485 - accuracy: 0.98
88 - val_loss: 0.1224 - val_accuracy: 0.8622
Epoch 12/20
30/30 [============== ] - 1s 21ms/step - loss: 0.0460 - accuracy: 0.99
01 - val_loss: 0.1251 - val_accuracy: 0.8561
Epoch 13/20
30/30 [============== ] - 1s 28ms/step - loss: 0.0437 - accuracy: 0.99
16 - val loss: 0.1276 - val accuracy: 0.8521
Epoch 14/20
35 - val_loss: 0.1294 - val_accuracy: 0.8499
Epoch 15/20
30/30 [============== ] - 1s 30ms/step - loss: 0.0393 - accuracy: 0.99
49 - val_loss: 0.1322 - val_accuracy: 0.8473
Epoch 16/20
30/30 [============== ] - 1s 29ms/step - loss: 0.0375 - accuracy: 0.99
55 - val loss: 0.1342 - val accuracy: 0.8447
Epoch 17/20
30/30 [============== ] - 1s 23ms/step - loss: 0.0360 - accuracy: 0.99
60 - val_loss: 0.1366 - val_accuracy: 0.8399
Epoch 18/20
30/30 [============== ] - 1s 26ms/step - loss: 0.0350 - accuracy: 0.99
67 - val loss: 0.1389 - val accuracy: 0.8369
Epoch 19/20
30/30 [============== ] - 1s 23ms/step - loss: 0.0335 - accuracy: 0.99
67 - val_loss: 0.1420 - val_accuracy: 0.8324
Epoch 20/20
67 - val_loss: 0.1425 - val_accuracy: 0.8329
```

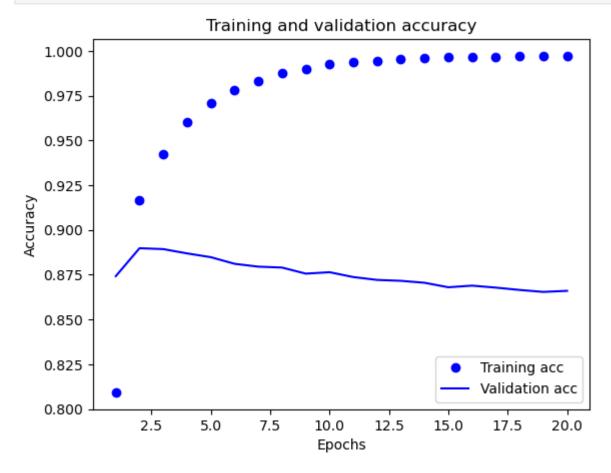
```
In [130... plt.clf()
    acc = history_dict["accuracy"]
    val_acc = history_dict["val_accuracy"]
    plt.plot(epochs, acc, "bo", label="Training acc")
    plt.plot(epochs, val_acc, "b", label="Validation acc")
    plt.title("Training and validation accuracy")
    plt.xlabel("Epochs")
    plt.ylabel("Accuracy")
    plt.legend()
    plt.show()
```



```
results = model_one_hidden_layer.evaluate(imdb_test,value_test)
In [131...
         # Adding more hidden layers to examine how it affects the accuracy. Here three hidden
In [132...
         from keras.models import Sequential
         from keras.layers import Dense, Dropout
         from keras import regularizers
         model_three_hidden_layers = Sequential()
         model_three_hidden_layers.add(Dense(32, activation='tanh', activity_regularizer=regula
         model three hidden layers.add(Dropout(0.5))
         model three hidden layers.add(Dense(32, activation='tanh', activity regularizer=regula
         model three hidden layers.add(Dropout(0.5))
         model_three_hidden_layers.add(Dense(32, activation='tanh', activity_regularizer=regula
         model three hidden layers.add(Dropout(0.5))
         model three hidden layers.add(Dense(1, activation='sigmoid')) # Output Layer
```

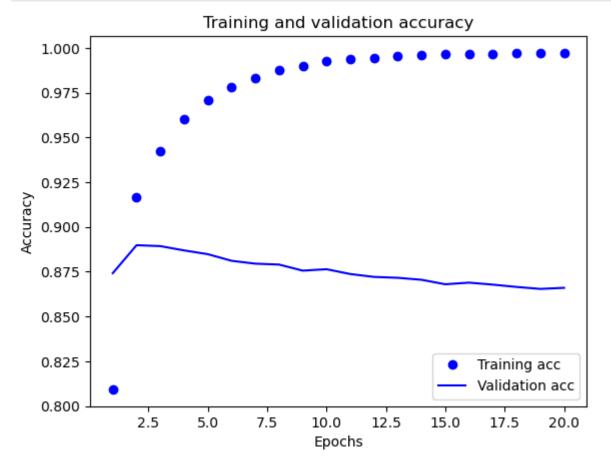
```
Epoch 1/20
30/30 [=============== ] - 5s 85ms/step - loss: 0.2446 - accuracy: 0.70
59 - val loss: 0.1605 - val accuracy: 0.8634
Epoch 2/20
30/30 [================ ] - 1s 23ms/step - loss: 0.1744 - accuracy: 0.87
83 - val loss: 0.1401 - val accuracy: 0.8788
Epoch 3/20
30/30 [============ ] - 1s 31ms/step - loss: 0.1466 - accuracy: 0.90
87 - val loss: 0.1371 - val accuracy: 0.8754
Epoch 4/20
30/30 [=============== ] - 1s 27ms/step - loss: 0.1294 - accuracy: 0.92
55 - val_loss: 0.1372 - val_accuracy: 0.8711
Epoch 5/20
30/30 [============== ] - 1s 32ms/step - loss: 0.1162 - accuracy: 0.93
97 - val loss: 0.1398 - val accuracy: 0.8646
Epoch 6/20
30/30 [============== ] - 1s 27ms/step - loss: 0.1084 - accuracy: 0.94
57 - val_loss: 0.1395 - val_accuracy: 0.8621
Epoch 7/20
30/30 [============= ] - 1s 29ms/step - loss: 0.1013 - accuracy: 0.95
06 - val loss: 0.1398 - val accuracy: 0.8581
30/30 [============== ] - 1s 24ms/step - loss: 0.0947 - accuracy: 0.95
65 - val loss: 0.1409 - val accuracy: 0.8594
Epoch 9/20
30/30 [============== ] - 1s 30ms/step - loss: 0.0892 - accuracy: 0.96
07 - val loss: 0.1420 - val accuracy: 0.8531
Epoch 10/20
30/30 [=============== ] - 1s 24ms/step - loss: 0.0851 - accuracy: 0.96
33 - val loss: 0.1426 - val accuracy: 0.8509
Epoch 11/20
30/30 [=============== ] - 1s 25ms/step - loss: 0.0806 - accuracy: 0.96
65 - val_loss: 0.1464 - val_accuracy: 0.8454
Epoch 12/20
30/30 [============== ] - 1s 27ms/step - loss: 0.0747 - accuracy: 0.97
29 - val_loss: 0.1483 - val_accuracy: 0.8422
Epoch 13/20
30/30 [============== ] - 1s 31ms/step - loss: 0.0721 - accuracy: 0.97
37 - val loss: 0.1467 - val accuracy: 0.8440
Epoch 14/20
30/30 [============== ] - 1s 23ms/step - loss: 0.0687 - accuracy: 0.97
66 - val_loss: 0.1482 - val_accuracy: 0.8407
Epoch 15/20
30/30 [============== ] - 1s 28ms/step - loss: 0.0655 - accuracy: 0.97
72 - val_loss: 0.1498 - val_accuracy: 0.8381
Epoch 16/20
30/30 [============== ] - 1s 24ms/step - loss: 0.0618 - accuracy: 0.97
99 - val loss: 0.1503 - val accuracy: 0.8377
Epoch 17/20
30/30 [=============== ] - 1s 27ms/step - loss: 0.0602 - accuracy: 0.98
15 - val_loss: 0.1518 - val_accuracy: 0.8332
Epoch 18/20
30/30 [=============== ] - 1s 30ms/step - loss: 0.0586 - accuracy: 0.98
28 - val loss: 0.1530 - val accuracy: 0.8332
Epoch 19/20
30/30 [=============== ] - 1s 39ms/step - loss: 0.0564 - accuracy: 0.98
31 - val loss: 0.1546 - val accuracy: 0.8298
Epoch 20/20
30/30 [============== ] - 1s 43ms/step - loss: 0.0541 - accuracy: 0.98
58 - val_loss: 0.1539 - val_accuracy: 0.8304
```

```
In [133...
plt.clf()
acc = history_dict["accuracy"]
val_acc = history_dict["val_accuracy"]
plt.plot(epochs, acc, "bo", label="Training acc")
plt.plot(epochs, val_acc, "b", label="Validation acc")
plt.title("Training and validation accuracy")
plt.xlabel("Epochs")
plt.ylabel("Accuracy")
plt.legend()
plt.show()
```



```
Epoch 1/20
30/30 [=============== ] - 3s 53ms/step - loss: 0.1677 - accuracy: 0.80
76 - val_loss: 0.1254 - val_accuracy: 0.8801
Epoch 2/20
30/30 [================ ] - 1s 25ms/step - loss: 0.1033 - accuracy: 0.92
12 - val loss: 0.1160 - val accuracy: 0.8900
Epoch 3/20
30/30 [============== ] - 1s 35ms/step - loss: 0.0849 - accuracy: 0.94
48 - val loss: 0.1147 - val accuracy: 0.8839
Epoch 4/20
30/30 [============== ] - 1s 38ms/step - loss: 0.0722 - accuracy: 0.96
29 - val_loss: 0.1154 - val_accuracy: 0.8790
Epoch 5/20
30/30 [============== ] - 1s 35ms/step - loss: 0.0639 - accuracy: 0.97
25 - val loss: 0.1179 - val accuracy: 0.8742
Epoch 6/20
30/30 [============== ] - 1s 44ms/step - loss: 0.0576 - accuracy: 0.97
81 - val_loss: 0.1206 - val_accuracy: 0.8689
Epoch 7/20
30/30 [============== ] - 1s 45ms/step - loss: 0.0520 - accuracy: 0.98
39 - val loss: 0.1238 - val accuracy: 0.8636
30/30 [============== ] - 1s 39ms/step - loss: 0.0480 - accuracy: 0.98
79 - val loss: 0.1268 - val accuracy: 0.8584
Epoch 9/20
30/30 [============== ] - 1s 34ms/step - loss: 0.0448 - accuracy: 0.98
89 - val loss: 0.1294 - val accuracy: 0.8553
Epoch 10/20
30/30 [============== ] - 1s 38ms/step - loss: 0.0422 - accuracy: 0.99
15 - val loss: 0.1327 - val accuracy: 0.8488
Epoch 11/20
30/30 [============== ] - 1s 33ms/step - loss: 0.0394 - accuracy: 0.99
31 - val_loss: 0.1383 - val_accuracy: 0.8404
Epoch 12/20
30/30 [============== ] - 1s 38ms/step - loss: 0.0374 - accuracy: 0.99
43 - val_loss: 0.1413 - val_accuracy: 0.8349
Epoch 13/20
30/30 [============== ] - 1s 36ms/step - loss: 0.0360 - accuracy: 0.99
41 - val loss: 0.1431 - val accuracy: 0.8359
Epoch 14/20
30/30 [============== ] - 1s 37ms/step - loss: 0.0344 - accuracy: 0.99
52 - val_loss: 0.1465 - val_accuracy: 0.8326
Epoch 15/20
30/30 [============== ] - 1s 34ms/step - loss: 0.0329 - accuracy: 0.99
65 - val_loss: 0.1482 - val_accuracy: 0.8293
Epoch 16/20
30/30 [============== ] - 1s 36ms/step - loss: 0.0312 - accuracy: 0.99
71 - val loss: 0.1515 - val accuracy: 0.8268
Epoch 17/20
30/30 [============== ] - 1s 35ms/step - loss: 0.0302 - accuracy: 0.99
71 - val_loss: 0.1552 - val_accuracy: 0.8240
Epoch 18/20
30/30 [============== ] - 1s 38ms/step - loss: 0.0294 - accuracy: 0.99
67 - val loss: 0.1570 - val accuracy: 0.8221
Epoch 19/20
30/30 [============== ] - 1s 37ms/step - loss: 0.0284 - accuracy: 0.99
73 - val_loss: 0.1595 - val_accuracy: 0.8186
Epoch 20/20
30/30 [============== ] - 1s 43ms/step - loss: 0.0278 - accuracy: 0.99
74 - val_loss: 0.1610 - val_accuracy: 0.8176
```

```
In [136... plt.clf()
    acc = history_dict["accuracy"]
    val_acc = history_dict["val_accuracy"]
    plt.plot(epochs, acc, "bo", label="Training acc")
    plt.plot(epochs, val_acc, "b", label="Validation acc")
    plt.title("Training and validation accuracy")
    plt.xlabel("Epochs")
    plt.ylabel("Accuracy")
    plt.legend()
    plt.show()
```



- Neural Network Configurations for IMDB Sentiment Analysis
- Introduction

This report presents the results of training several neural network models with different configurations for sentiment analysis on the IMDB dataset. The goal is to determine the optimal model architecture for accurately classifying movie reviews as positive or negative.

Experimental Setup

Dataset: The IMDB dataset consists of 50,000 movie reviews labeled as positive or negative. Model Configurations: Four different neural network configurations were evaluated: One hidden

layer with 32 units and Tanh activation function One hidden layer with 32 units, Tanh activation function, and dropout regularization Three hidden layers with 32 units each, Tanh activation function, and dropout regularization One hidden layer with 64 units, Tanh activation function, and dropout regularization

- Results and Analysis
- Model 1: One Hidden Layer (32 Units, Tanh Activation) Accuracy: 85.54% Validation
 Accuracy: 86.60% Observations: The model shows a good performance with decent
 accuracy on both training and validation sets. However, there is a slight overfitting as the
 training accuracy is slightly higher than the validation accuracy.
- Model 2: One Hidden Layer (32 Units, Tanh Activation, Dropout Regularization) Accuracy: 81.88% Validation Accuracy: 83.29% Observations: Introducing dropout regularization slightly reduces overfitting compared to Model 1, but there is still room for improvement in validation accuracy.
- Model 3: Three Hidden Layers (32 Units, Tanh Activation, Dropout Regularization) Accuracy: 81.14% Validation Accuracy: 83.04% Observations: Adding more hidden layers does not significantly improve performance. The model seems to suffer from overfitting, similar to Model 2.
- Model 4: One Hidden Layer (64 Units, Tanh Activation, Dropout Regularization) Accuracy: 80.02% Validation Accuracy: 81.76% Observations: Increasing the number of units in the hidden layer does not lead to better performance. The model exhibits similar overfitting issues as previous configurations.

Model	Validation Accuracy	Test Loss	Test Accuracy
One Hidden Layer (32 units)	0.8660	0.1132	0.8554
One Hidden Layer (32 units)	0.8329	0.1526	0.8188
Three Hidden Layers (32 units)	0.8304	0.1644	0.8114
One Hidden Layer (64 units)	0.8176	0.1711	0.8002

Conclusion

Based on the experiments conducted, the model with one hidden layer consisting of 32 units and Tanh activation function (Model 1) performs the best, achieving the highest accuracy on both the training and validation sets. Introducing dropout regularization helps mitigate overfitting to some extent, but adding more hidden layers or increasing the number of units does not yield significant improvements. Therefore, Model 1 is recommended as the optimal configuration for sentiment analysis on the IMDB dataset. However, further experimentation with hyperparameter tuning and different architectures could potentially lead to even better results.