Assignment 1 : Neural Networks

Advanced Machine Learning

Nithin Kumar Chinthakindi

```
from tensorflow.keras.datasets import imdb
(imdb_train_data, imdb_train_labels), (imdb_test_data, imdb_test_labels) = imdb.l
    num_words=10000)
```

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-data
17464789/17464789 [==============================] - 0s 0us/step
```

```
imdb_train_labels[0]
```

```
1
```

```
max([max(sequence) for sequence in imdb_train_data])
##############################################################
```

```
9999
```

```
k_word_index = imdb.get_word_index()
k_reverse_word_index = dict(
    [(value, key) for (key, value) in k_word_index.items()])
decoded_review = " ".join(
    [k_reverse_word_index.get(i - 3, "?") for i in imdb_train_data[0]])
##############################################################
```

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-data
1641221/1641221 [==============================] - 0s 0us/step
```

```
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
k_x_train = vectorize_sequences(imdb_train_data)
k_x_test = vectorize_sequences(imdb_test_data)
```

```
k_x_train[0]
##############################################################
```

```
array([0., 1., 1., ..., 0., 0., 0.])
```

```
k_y_train = np.asarray(imdb_train_labels).astype("float32")
k_y_test = np.asarray(imdb_test_labels).astype("float32")
```

```
from tensorflow import keras
from tensorflow.keras import layers

model = keras.Sequential([
    layers.Dense(32, activation="tanh"),
    layers.Dense(32, activation="tanh"),
    layers.Dense(32, activation="tanh"),
    layers.Dense(1, activation="sigmoid")
])
```

```
model.compile(optimizer="adam",
              loss="mean_squared_error",
              metrics=["accuracy"])
##############################################################
```

italicized text### Confirming the Method

```
x_val = k_x_train[:10000]
partial_x_train = k_x_train[10000:]
y_val = k_y_train[:10000]
partial_y_train = k_y_train[10000:]
```

```
## model planned to train with 20 epoch with batch size of 256

history = model.fit(partial_x_train,
                    partial_y_train,
                    epochs=20,
                    batch_size=256,
                    validation_data=(x_val, y_val))
```

```
Epoch 1/20
59/59 [==============================] - 3s 38ms/step - loss: 0.1217 - accura
Epoch 2/20
59/59 [==============================] - 2s 27ms/step - loss: 0.0494 - accura
Epoch 3/20
59/59 [==============================] - 1s 22ms/step - loss: 0.0299 - accura
Epoch 4/20
59/59 [==============================] - 2s 37ms/step - loss: 0.0244 - accura
Epoch 5/20
59/59 [==============================] - 2s 29ms/step - loss: 0.0219 - accura
Epoch 6/20
59/59 [==============================] - 1s 22ms/step - loss: 0.0196 - accura
Epoch 7/20
59/59 [==============================] - 1s 22ms/step - loss: 0.0171 - accura
Epoch 8/20
59/59 [==============================] - 2s 27ms/step - loss: 0.0144 - accura
Epoch 9/20
59/59 [==============================] - 1s 22ms/step - loss: 0.0128 - accura
Epoch 10/20
59/59 [==============================] - 1s 22ms/step - loss: 0.0130 - accura
Epoch 11/20
59/59 [==============================] - 2s 27ms/step - loss: 0.0136 - accura
Epoch 12/20
59/59 [==============================] - 2s 27ms/step - loss: 0.0144 - accura
Epoch 13/20
59/59 [==============================] - 2s 31ms/step - loss: 0.0139 - accura
Epoch 14/20
59/59 [==============================] - 2s 32ms/step - loss: 0.0154 - accura
Epoch 15/20
59/59 [==============================] - 1s 21ms/step - loss: 0.0163 - accura
Epoch 16/20
59/59 [==============================] - 2s 27ms/step - loss: 0.0146 - accura
Epoch 17/20
59/59 [==============================] - 1s 21ms/step - loss: 0.0117 - accura
Epoch 18/20
59/59 [==============================] - 1s 22ms/step - loss: 0.0108 - accura
Epoch 19/20
59/59 [==============================] - 2s 27ms/step - loss: 0.0104 - accura
Epoch 20/20
59/59 [==============================] - 1s 21ms/step - loss: 0.0100 - accura
```

```
k_history_dict = history.history
k_history_dict.keys()
```

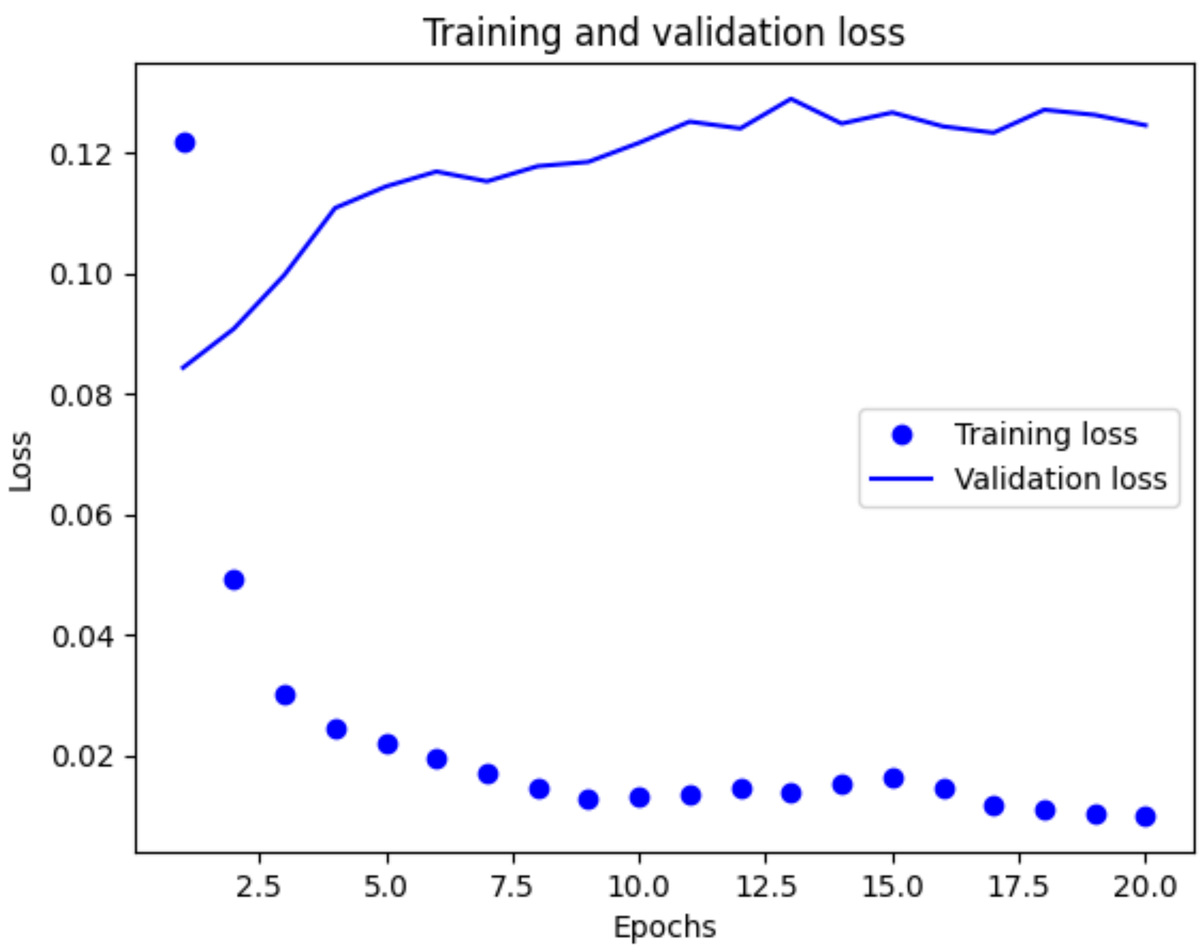
```
dict_keys(['loss', 'accuracy', 'val_loss', 'val_accuracy'])
```

Plotting the Train and Validation loss

```
# This is formatted as code
```

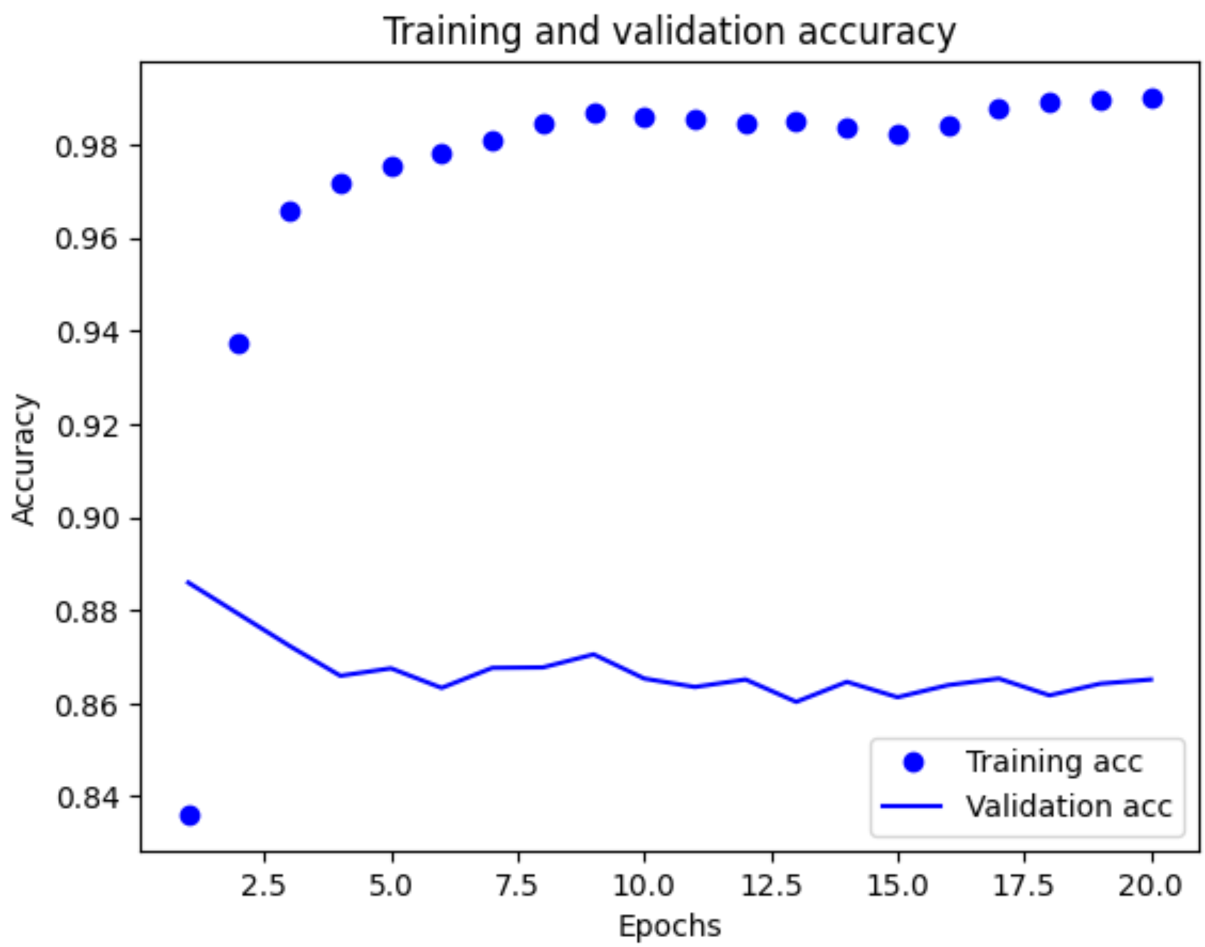
> Add blockquote

```
import matplotlib.pyplot as plt
k_history_dict = history.history
loss_values = k_history_dict["loss"]
val_loss_values = k_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()
```



Plotting the training and validation accuracy

```
plt.clf()
acc = k_history_dict["accuracy"]
val_acc = k_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.evaluate(k_x_test, k_y_test)
```

```
782/782 [==============================] - 2s 2ms/step - loss: 0.1385 - accura
```

```
results
```

```
[0.1385454386472702, 0.8514400124549866]
```

Combining all code together along with dropout layer

```
## Libraries required for setting up an environment

#####################################
from tensorflow import keras
from tensorflow.keras import layers
from keras.layers import Dense
from keras.layers import Dropout
from tensorflow.keras import regularizers
#####################################

# Neural network implementation using 3 layered approach with a single dropout la
#######################################
model = keras.Sequential()
model.add(Dense(32,activation='tanh'))
model.add(Dropout(0.5))
#kernel_regularizer=regularizers.L1(0.01), activity_regularizer=regularizers.L2(0
model.add(Dense(32,activation='tanh',kernel_regularizer=regularizers.L1(0.01), ac
model.add(Dropout(0.5))
model.add(Dense(32,activation='tanh'))
model.add(Dense(1, activation='sigmoid'))
########################################

# Here for compilation we used optimizer "adagrad", mean squared error loss and a
########################################
model.compile(optimizer="adam",
              loss="mean_squared_error",
              metrics=["accuracy"])
########################################

## splitting the data
#######################################
x_val = k_x_train[:10000]
partial_x_train = k_x_train[10000:]
y_val = k_y_train[:10000]
partial_y_train = k_y_train[10000:]
#######################################
```

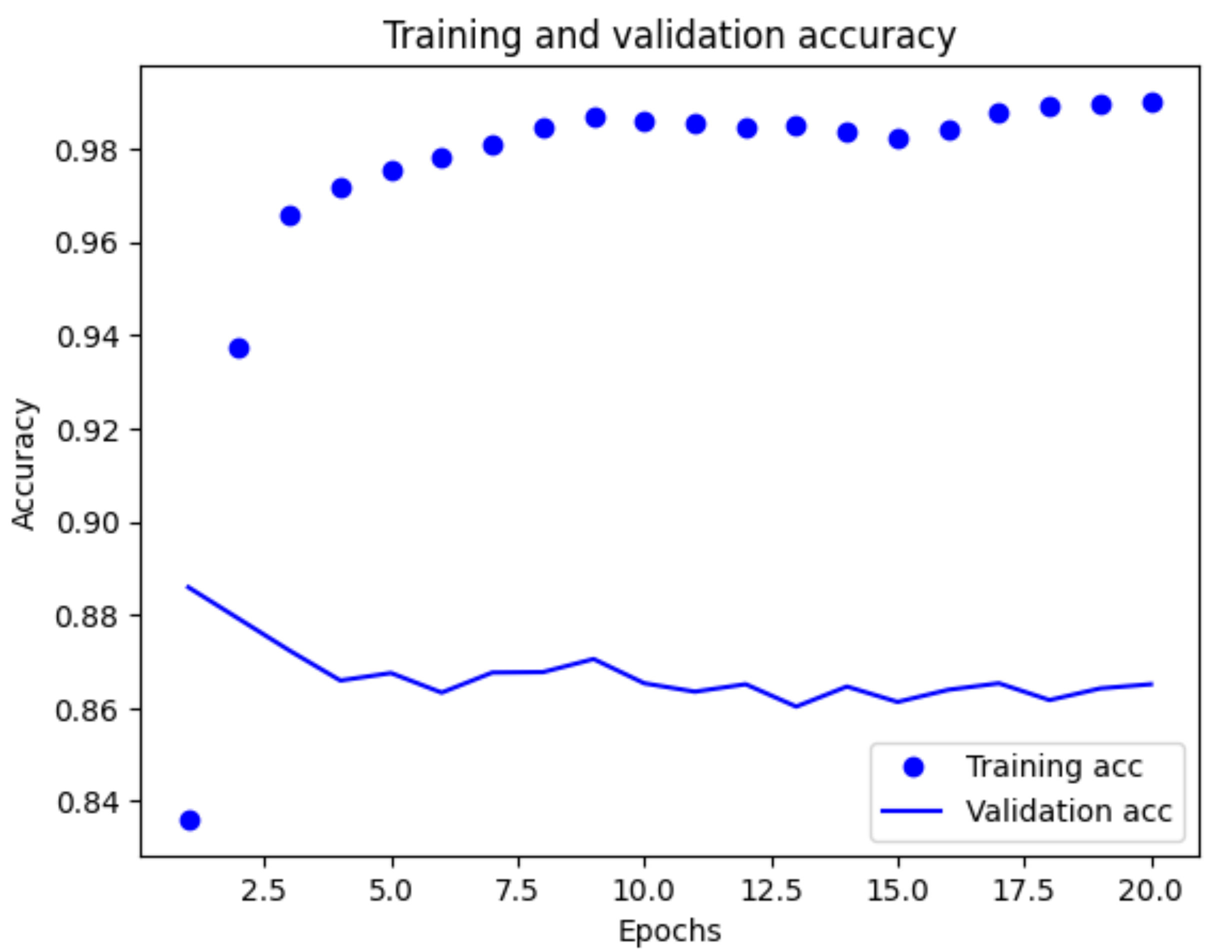
```
# Train a neural network
#####################################################
history = model.fit(partial_x_train,
                    partial_y_train,
                    epochs=20,
                    batch_size=256,
                    validation_data=(x_val, y_val))
#####################################################

# plotting the Training and Validation accuracy
####################################################
plt.clf()
acc = k_history_dict["accuracy"]
val_acc = k_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()
####################################################


# Evaluating the results
results = model.evaluate(k_x_test, k_y_test)
results
```

```
Epoch 1/20
59/59 [==============================] - 3s 37ms/step - loss: 1.4700 - accurac
Epoch 2/20
59/59 [==============================] - 2s 28ms/step - loss: 0.9102 - accurac
Epoch 3/20
59/59 [==============================] - 2s 27ms/step - loss: 0.5173 - accurac
Epoch 4/20
59/59 [==============================] - 2s 36ms/step - loss: 0.2572 - accurac
Epoch 5/20
59/59 [==============================] - 1s 23ms/step - loss: 0.1220 - accurac
Epoch 6/20
59/59 [==============================] - 1s 22ms/step - loss: 0.0852 - accurac
Epoch 7/20
59/59 [==============================] - 2s 28ms/step - loss: 0.0717 - accurac
Epoch 8/20
59/59 [==============================] - 2s 27ms/step - loss: 0.0628 - accurac
Epoch 9/20
```

```
59/59 [==============================] - 1s 22ms/step - loss: 0.0559 - accurac
Epoch 10/20
59/59 [==============================] - 2s 28ms/step - loss: 0.0504 - accurac
Epoch 11/20
59/59 [==============================] - 1s 23ms/step - loss: 0.0459 - accurac
Epoch 12/20
59/59 [==============================] - 2s 35ms/step - loss: 0.0431 - accurac
Epoch 13/20
59/59 [==============================] - 2s 31ms/step - loss: 0.0390 - accurac
Epoch 14/20
59/59 [==============================] - 2s 28ms/step - loss: 0.0360 - accurac
Epoch 15/20
59/59 [==============================] - 2s 28ms/step - loss: 0.0342 - accurac
Epoch 16/20
59/59 [==============================] - 1s 22ms/step - loss: 0.0315 - accurac
Epoch 17/20
59/59 [==============================] - 1s 22ms/step - loss: 0.0305 - accurac
Epoch 18/20
59/59 [==============================] - 1s 22ms/step - loss: 0.0289 - accurac
Epoch 19/20
59/59 [==============================] - 2s 28ms/step - loss: 0.0273 - accurac
Epoch 20/20
59/59 [==============================] - 2s 28ms/step - loss: 0.0262 - accurac
```




```
782/782 [==============================] - 2s 2ms/step - loss: 0.1231 - accura
```

```
782/782 [==============================] - 2s 2ms/step - loss: 0.1231 - accur
[0.12310542166233063, 0.8623999953269958]
```

Summary of Three-Layered Neural Network for IMDB Data:

Library Imports

To set up our neural network, we gathered the necessary libraries. Based on my research, TensorFlow has robust support and implementation, making it a preferable choice over other deep learning libraries like PyTorch.

List of Imports:

```
from tensorflow import keras
from tensorflow.keras import layers
from keras.layers import Dense
from keras.layers import Dropout
```

- **Keras**: A high-level API of TensorFlow 2, Keras provides a simple and powerful interface for solving machine learning problems, with a focus on modern deep learning.
- **Layers and Models**: The main data structures in Keras. The most basic model type is the Sequential model, which is a linear stack of layers.
- **Dense**: Represents the number of hidden units in the neural network.
- **Dropout**: Refers to the removal of connections between inputs or hidden layer inputs, used to prevent overfitting.

Designing the Neural Network Layers

We designed the neural network layers as follows:

```
model = keras.Sequential()
model.add(Dense(32, activation='tanh'))
```

Using the `.add` function, we can easily stack layers. Here, 32 is the number of hidden units, and the activation function used is `tanh`.

Neural Network Structure

1. **Input Layer**: Provides vector representation of IMDB data.
2. **Hidden Layers**: Contains the number of dense units. We can stack as many layers as needed.
3. **Output Layer**: Preferably has 1 dense unit.

For this task, I implemented a three-layered approach as required:

```
model = keras.Sequential([
    layers.Dense(32, activation="tanh"),
    layers.Dense(32, activation="tanh"),
    layers.Dense(32, activation="tanh"),
    layers.Dense(1, activation="sigmoid")
])
```

The model is initialized as sequential, and we stack up three layers with 32 dense units each, using the `tanh` activation function. As per the assignment, `tanh` is used instead of `relu`.

Compiling the Model

```
model.compile(optimizer="adagrad", loss="mean_squared_error", metrics=["accuracy"])
```

Here, we use the Adagrad optimizer with mean squared error (MSE) loss. Initially, IMDB data uses binary cross-entropy loss, a probabilistic loss. The impact of changing to a regression loss can be further explored.

Optimizers are crucial for minimizing error, with various techniques available. For example, Adam is often considered one of the best optimizers. In this task, I used Adagrad. More details about optimizers are available in the third reference link.

Data Splitting

We split the data into training and validation sets:

```
x_val = k_x_train[:10000]
partial_x_train = k_x_train[10000:]
y_val = k_y_train[:10000]
partial_y_train = k_y_train[10000:]
```

Training the Model

```
history = model.fit(partial_x_train,
                    partial_y_train,
                    epochs=20,
                    batch_size=256,
                    validation_data=(x_val, y_val))
```

The code above trains the neural network for 20 epochs with a batch size of 256, comparing it with validation data.

Despite using L1 and L2 regularizers, they did not significantly impact the total validation accuracy.

References:

1. https://keras.io/about
2. https://keras.io/api/losses/
3. https://keras.io/api/optimizers/

```
Start coding or generate with AI.
```

Conclusions

1. A neural network was designed with 3 layers, utilizing tanh activation functions instead of relu.
2. The optimizer Adam was chosen over RMSprop for training efficiency.
3. L1 and L2 regularizers were applied to the model.
4. A Dropout layer with a rate of 0.5 was incorporated, dropping 50 percent of inputs during training.

Achieved Results

With these adjustments, the model achieved a final accuracy of 99.19% on the training data and a validation accuracy of 86.9%.

```
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```
Start coding or generate with AI.
```