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1 Tuning Neural Networks with Regularization - Lab

1.1 Introduction

In this lab, you'll use a train-test partition as well as a validation set to get better insights about how to tune neural networks using regularization techniques. You'll start by repeating the process from the last section: importing the data and performing preprocessing including one-hot encoding. From there, you'll define and compile the model like before.

1.2 Objectives

You will be able to:

- Apply early stopping criteria with a neural network
- Apply L1, L2, and dropout regularization on a neural network
- Examine the effects of training with more data on a neural network

1.3 Load the Data

Run the following cell to import some of the libraries and classes you'll need in this lab.

```
[1]: import pandas as pd
  import numpy as np
  import random
  import matplotlib.pyplot as plt
  %matplotlib inline
  from sklearn.model_selection import train_test_split
  from keras.utils.np_utils import to_categorical
  from sklearn.preprocessing import LabelBinarizer
  from keras.preprocessing.text import Tokenizer

import warnings
  warnings.filterwarnings(action='ignore', category=FutureWarning)
```

The data is stored in the file 'Bank_complaints.csv'. Load and preview the dataset.

```
[2]: # Load and preview the dataset
df = pd.read_csv('Bank_complaints.csv')
df.head()
```

```
[2]: Product Consumer complaint narrative

0 Student loan In XX/XX/XXXX I filled out the Fedlaon applica...

1 Student loan I am being contacted by a debt collector for p...

2 Student loan I cosigned XXXX student loans at SallieMae for...

3 Student loan Navient has sytematically and illegally failed...

4 Student loan My wife became eligible for XXXX Loan Forgiven...
```

1.4 Preprocessing Overview

Before you begin to practice some of your new tools such as regularization and optimization, let's practice munging some data as you did in the previous section with bank complaints. Recall some techniques:

- Sampling in order to reduce training time (investigate model accuracy vs data size later on)
- Train test split
- One-hot encoding your complaint text
- Transforming your category labels

1.5 Preprocessing: Generate a Random Sample

Since you have quite a bit of data and training neural networks takes a substantial amount of time and resources, downsample in order to test your initial pipeline. Going forward, these can be interesting areas of investigation: how does your model's performance change as you increase (or decrease) the size of your dataset?

- Generate a random sample of 10,000 observations using seed 123 for consistency of results.
- Split this sample into X and y

```
[3]: # Downsample the data
df_sample = df.sample(10000, random_state = 123)

# Split the data into X and y
y = df_sample["Product"]

X = df_sample['Consumer complaint narrative']

### The Following Does Not Work
# X2 = df_sample.drop("Product", axis = 1)
```

1.6 Train-test split

- Split the data into training and test sets
- Assign 1500 obervations to the test set and use 42 as the seed

```
[4]: # Split data into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 1500, random_state = 42)
```

1.7 Validation set

As mentioned in the previous lesson, it is good practice to set aside a validation set, which is then used during hyperparameter tuning. Afterwards, when you have decided upon a final model, the test set can then be used to determine an unbiased perforance of the model.

Run the cell below to further divide the training data into training and validation sets.

1.8 Preprocessing: One-hot Encoding the Complaints

As before, you need to do some preprocessing before building a neural network model.

- Keep the 2,000 most common words and use one-hot encoding to reformat the complaints into a matrix of vectors
- Transform the training, validate, and test sets

```
[6]: # Use one-hot encoding to reformat the complaints into a matrix of vectors
# Only keep the 2000 most common words

tokenizer = Tokenizer(num_words = 2000)
tokenizer.fit_on_texts(X_train_final)

X_train_tokens = tokenizer.texts_to_matrix(X_train_final, mode = 'binary')
X_val_tokens = tokenizer.texts_to_matrix(X_val, mode = 'binary')
X_test_tokens = tokenizer.texts_to_matrix(X_test, mode = 'binary')
```

1.9 Preprocessing: Encoding the Products

Similarly, now transform the descriptive product labels to integers labels. After transforming them to integer labels, retransform them into a matrix of binary flags, one for each of the various product labels.

Note: This is similar to your previous work with dummy variables. Each of the various product categories will be its own column, and each observation will be a row. In turn, each of these observation rows will have a 1 in the column associated with it's label, and all other entries for the row will be zero.

Transform the training, validate, and test sets.

```
[7]: # Transform the product labels to numerical values
lb = LabelBinarizer()
lb.fit(y_train_final)
```

```
y_train_lb = to_categorical(lb.transform(y_train_final))[:,:,1]
y_val_lb = to_categorical(lb.transform(y_val))[:,:,1]
y_test_lb = to_categorical(lb.transform(y_test))[:,:,1]
```

1.10 A Baseline Model

Rebuild a fully connected (Dense) layer network:

- Use 2 hidden layers with 50 units in the first and 25 in the second layer, both with 'relu' activation functions (since you are dealing with a multiclass problem, classifying the complaints into 7 classes) - Use a 'softmax' activation function for the output layer

```
[8]: X_train_tokens.shape[1]
```

[8]: 2000

1.10.1 Compile the Model

Compile this model with:

- a stochastic gradient descent optimizer
- 'categorical_crossentropy' as the loss function
- a focus on 'accuracy'

1.10.2 Train the Model

- Train the model for 150 epochs in mini-batches of 256 samples
- Include the validation_data argument to ensure you keep track of the validation loss

```
epochs=150,
batch_size=256,
validation_data=(X_val_tokens,u
```

```
Epoch 1/150
0.1489 - val_loss: 1.9482 - val_acc: 0.1450
Epoch 2/150
0.1731 - val_loss: 1.9308 - val_acc: 0.1980
Epoch 3/150
0.2145 - val_loss: 1.9151 - val_acc: 0.2280
Epoch 4/150
0.2491 - val_loss: 1.8968 - val_acc: 0.2450
Epoch 5/150
0.2728 - val_loss: 1.8739 - val_acc: 0.2720
30/30 [================== ] - 0s 3ms/step - loss: 1.8487 - acc:
0.2971 - val_loss: 1.8460 - val_acc: 0.2980
Epoch 7/150
0.3212 - val_loss: 1.8125 - val_acc: 0.3170
Epoch 8/150
0.3440 - val_loss: 1.7737 - val_acc: 0.3420
Epoch 9/150
30/30 [============ ] - Os 3ms/step - loss: 1.7365 - acc:
0.3712 - val_loss: 1.7322 - val_acc: 0.3600
Epoch 10/150
0.3961 - val_loss: 1.6882 - val_acc: 0.3840
Epoch 11/150
0.4181 - val_loss: 1.6428 - val_acc: 0.4120
Epoch 12/150
0.4479 - val_loss: 1.5961 - val_acc: 0.4410
Epoch 13/150
0.4792 - val_loss: 1.5487 - val_acc: 0.4680
Epoch 14/150
0.5061 - val_loss: 1.5003 - val_acc: 0.5040
```

```
Epoch 15/150
0.5367 - val_loss: 1.4541 - val_acc: 0.5160
Epoch 16/150
0.5585 - val_loss: 1.4073 - val_acc: 0.5480
Epoch 17/150
0.5776 - val_loss: 1.3617 - val_acc: 0.5640
Epoch 18/150
0.5979 - val_loss: 1.3176 - val_acc: 0.5810
Epoch 19/150
30/30 [============= ] - Os 3ms/step - loss: 1.2660 - acc:
0.6160 - val_loss: 1.2753 - val_acc: 0.5890
Epoch 20/150
0.6273 - val_loss: 1.2357 - val_acc: 0.6060
Epoch 21/150
0.6396 - val_loss: 1.1995 - val_acc: 0.6110
Epoch 22/150
0.6472 - val_loss: 1.1621 - val_acc: 0.6280
Epoch 23/150
30/30 [============= ] - Os 3ms/step - loss: 1.1109 - acc:
0.6580 - val_loss: 1.1292 - val_acc: 0.6360
Epoch 24/150
0.6672 - val_loss: 1.0980 - val_acc: 0.6520
Epoch 25/150
0.6756 - val_loss: 1.0678 - val_acc: 0.6540
Epoch 26/150
0.6819 - val_loss: 1.0419 - val_acc: 0.6560
Epoch 27/150
0.6855 - val_loss: 1.0177 - val_acc: 0.6680
Epoch 28/150
0.6923 - val_loss: 0.9932 - val_acc: 0.6680
Epoch 29/150
30/30 [============= ] - Os 3ms/step - loss: 0.9395 - acc:
0.6981 - val_loss: 0.9708 - val_acc: 0.6760
Epoch 30/150
30/30 [============= ] - Os 3ms/step - loss: 0.9171 - acc:
0.7043 - val_loss: 0.9531 - val_acc: 0.6760
```

```
Epoch 31/150
30/30 [============= ] - Os 3ms/step - loss: 0.8961 - acc:
0.7115 - val_loss: 0.9346 - val_acc: 0.6830
Epoch 32/150
30/30 [================== ] - 0s 3ms/step - loss: 0.8767 - acc:
0.7149 - val_loss: 0.9132 - val_acc: 0.6910
Epoch 33/150
0.7213 - val_loss: 0.8997 - val_acc: 0.6890
Epoch 34/150
0.7239 - val_loss: 0.8845 - val_acc: 0.6950
Epoch 35/150
0.7292 - val_loss: 0.8715 - val_acc: 0.6920
Epoch 36/150
30/30 [============= ] - Os 3ms/step - loss: 0.8094 - acc:
0.7337 - val_loss: 0.8599 - val_acc: 0.7010
Epoch 37/150
0.7360 - val_loss: 0.8472 - val_acc: 0.6960
Epoch 38/150
0.7380 - val_loss: 0.8352 - val_acc: 0.7000
Epoch 39/150
30/30 [============ ] - Os 3ms/step - loss: 0.7694 - acc:
0.7441 - val_loss: 0.8270 - val_acc: 0.6980
Epoch 40/150
30/30 [============ ] - Os 3ms/step - loss: 0.7571 - acc:
0.7461 - val_loss: 0.8187 - val_acc: 0.7010
Epoch 41/150
0.7500 - val_loss: 0.8056 - val_acc: 0.7060
Epoch 42/150
0.7520 - val_loss: 0.7992 - val_acc: 0.6970
Epoch 43/150
0.7567 - val_loss: 0.7901 - val_acc: 0.7060
Epoch 44/150
0.7581 - val_loss: 0.7817 - val_acc: 0.7060
0.7579 - val_loss: 0.7763 - val_acc: 0.7120
Epoch 46/150
0.7605 - val_loss: 0.7765 - val_acc: 0.7070
```

```
Epoch 47/150
0.7629 - val_loss: 0.7630 - val_acc: 0.7080
Epoch 48/150
0.7667 - val_loss: 0.7590 - val_acc: 0.7160
Epoch 49/150
0.7685 - val_loss: 0.7507 - val_acc: 0.7130
Epoch 50/150
0.7725 - val_loss: 0.7453 - val_acc: 0.7180
Epoch 51/150
0.7741 - val_loss: 0.7428 - val_acc: 0.7150
Epoch 52/150
0.7764 - val_loss: 0.7354 - val_acc: 0.7180
Epoch 53/150
0.7779 - val_loss: 0.7304 - val_acc: 0.7180
Epoch 54/150
0.7801 - val_loss: 0.7337 - val_acc: 0.7180
Epoch 55/150
30/30 [============= ] - Os 3ms/step - loss: 0.6284 - acc:
0.7857 - val_loss: 0.7318 - val_acc: 0.7220
Epoch 56/150
30/30 [============= ] - Os 3ms/step - loss: 0.6223 - acc:
0.7856 - val_loss: 0.7194 - val_acc: 0.7240
Epoch 57/150
0.7879 - val_loss: 0.7185 - val_acc: 0.7200
Epoch 58/150
0.7909 - val_loss: 0.7165 - val_acc: 0.7300
Epoch 59/150
0.7924 - val_loss: 0.7091 - val_acc: 0.7270
Epoch 60/150
0.7963 - val_loss: 0.7108 - val_acc: 0.7290
0.7959 - val_loss: 0.7043 - val_acc: 0.7280
Epoch 62/150
0.8001 - val_loss: 0.7017 - val_acc: 0.7330
```

```
Epoch 63/150
0.7987 - val_loss: 0.7010 - val_acc: 0.7360
Epoch 64/150
0.8035 - val_loss: 0.6977 - val_acc: 0.7330
Epoch 65/150
0.8047 - val_loss: 0.6961 - val_acc: 0.7340
Epoch 66/150
0.8063 - val_loss: 0.6943 - val_acc: 0.7330
Epoch 67/150
0.8083 - val_loss: 0.6886 - val_acc: 0.7370
Epoch 68/150
0.8091 - val_loss: 0.6902 - val_acc: 0.7400
Epoch 69/150
0.8108 - val_loss: 0.6902 - val_acc: 0.7340
Epoch 70/150
0.8128 - val_loss: 0.6840 - val_acc: 0.7370
Epoch 71/150
0.8139 - val_loss: 0.6864 - val_acc: 0.7410
Epoch 72/150
0.8176 - val_loss: 0.6795 - val_acc: 0.7380
Epoch 73/150
0.8168 - val_loss: 0.6829 - val_acc: 0.7420
Epoch 74/150
0.8185 - val_loss: 0.6784 - val_acc: 0.7410
Epoch 75/150
0.8193 - val_loss: 0.6804 - val_acc: 0.7440
Epoch 76/150
0.8213 - val_loss: 0.6746 - val_acc: 0.7430
Epoch 77/150
0.8237 - val_loss: 0.6766 - val_acc: 0.7420
Epoch 78/150
0.8253 - val_loss: 0.6710 - val_acc: 0.7400
```

```
Epoch 79/150
0.8243 - val_loss: 0.6708 - val_acc: 0.7420
Epoch 80/150
0.8279 - val_loss: 0.6693 - val_acc: 0.7390
Epoch 81/150
0.8276 - val_loss: 0.6731 - val_acc: 0.7400
Epoch 82/150
0.8309 - val_loss: 0.6681 - val_acc: 0.7450
Epoch 83/150
30/30 [============= ] - Os 3ms/step - loss: 0.4953 - acc:
0.8317 - val_loss: 0.6683 - val_acc: 0.7400
Epoch 84/150
0.8319 - val_loss: 0.6643 - val_acc: 0.7390
Epoch 85/150
0.8336 - val_loss: 0.6652 - val_acc: 0.7450
Epoch 86/150
0.8356 - val_loss: 0.6686 - val_acc: 0.7460
Epoch 87/150
0.8395 - val_loss: 0.6667 - val_acc: 0.7460
Epoch 88/150
0.8387 - val_loss: 0.6670 - val_acc: 0.7460
Epoch 89/150
0.8389 - val_loss: 0.6622 - val_acc: 0.7490
Epoch 90/150
0.8415 - val_loss: 0.6594 - val_acc: 0.7430
Epoch 91/150
0.8436 - val_loss: 0.6594 - val_acc: 0.7430
Epoch 92/150
0.8440 - val_loss: 0.6617 - val_acc: 0.7460
Epoch 93/150
0.8456 - val_loss: 0.6607 - val_acc: 0.7410
Epoch 94/150
30/30 [============ ] - Os 3ms/step - loss: 0.4572 - acc:
0.8480 - val_loss: 0.6579 - val_acc: 0.7450
```

```
Epoch 95/150
0.8489 - val_loss: 0.6593 - val_acc: 0.7490
Epoch 96/150
0.8495 - val_loss: 0.6566 - val_acc: 0.7490
Epoch 97/150
0.8507 - val_loss: 0.6567 - val_acc: 0.7530
Epoch 98/150
0.8529 - val_loss: 0.6576 - val_acc: 0.7480
Epoch 99/150
0.8544 - val_loss: 0.6570 - val_acc: 0.7430
Epoch 100/150
0.8531 - val_loss: 0.6546 - val_acc: 0.7440
Epoch 101/150
0.8557 - val_loss: 0.6599 - val_acc: 0.7480
Epoch 102/150
0.8580 - val_loss: 0.6538 - val_acc: 0.7530
Epoch 103/150
30/30 [============= ] - Os 3ms/step - loss: 0.4290 - acc:
0.8599 - val_loss: 0.6558 - val_acc: 0.7480
Epoch 104/150
30/30 [============= ] - Os 3ms/step - loss: 0.4254 - acc:
0.8616 - val_loss: 0.6580 - val_acc: 0.7390
Epoch 105/150
30/30 [============= ] - Os 3ms/step - loss: 0.4223 - acc:
0.8625 - val_loss: 0.6568 - val_acc: 0.7410
Epoch 106/150
0.8629 - val_loss: 0.6529 - val_acc: 0.7510
Epoch 107/150
0.8643 - val_loss: 0.6539 - val_acc: 0.7490
Epoch 108/150
0.8655 - val_loss: 0.6546 - val_acc: 0.7530
Epoch 109/150
0.8663 - val_loss: 0.6592 - val_acc: 0.7470
Epoch 110/150
0.8684 - val_loss: 0.6583 - val_acc: 0.7440
```

```
Epoch 111/150
0.8696 - val_loss: 0.6558 - val_acc: 0.7470
Epoch 112/150
0.8703 - val_loss: 0.6569 - val_acc: 0.7390
Epoch 113/150
0.8715 - val_loss: 0.6559 - val_acc: 0.7570
Epoch 114/150
0.8729 - val_loss: 0.6567 - val_acc: 0.7540
Epoch 115/150
0.8731 - val_loss: 0.6572 - val_acc: 0.7530
Epoch 116/150
30/30 [============= ] - Os 3ms/step - loss: 0.3914 - acc:
0.8743 - val_loss: 0.6634 - val_acc: 0.7500
Epoch 117/150
0.8745 - val_loss: 0.6544 - val_acc: 0.7480
Epoch 118/150
0.8772 - val_loss: 0.6585 - val_acc: 0.7440
Epoch 119/150
0.8773 - val_loss: 0.6581 - val_acc: 0.7450
Epoch 120/150
0.8787 - val_loss: 0.6544 - val_acc: 0.7510
Epoch 121/150
0.8800 - val_loss: 0.6576 - val_acc: 0.7490
Epoch 122/150
0.8817 - val_loss: 0.6539 - val_acc: 0.7490
Epoch 123/150
0.8819 - val_loss: 0.6585 - val_acc: 0.7470
Epoch 124/150
0.8817 - val_loss: 0.6588 - val_acc: 0.7520
Epoch 125/150
30/30 [============= ] - Os 3ms/step - loss: 0.3677 - acc:
0.8839 - val_loss: 0.6561 - val_acc: 0.7510
Epoch 126/150
0.8844 - val_loss: 0.6579 - val_acc: 0.7440
```

```
Epoch 127/150
0.8855 - val_loss: 0.6594 - val_acc: 0.7510
Epoch 128/150
0.8852 - val_loss: 0.6612 - val_acc: 0.7480
Epoch 129/150
0.8875 - val_loss: 0.6594 - val_acc: 0.7470
Epoch 130/150
0.8877 - val_loss: 0.6617 - val_acc: 0.7510
Epoch 131/150
0.8900 - val_loss: 0.6612 - val_acc: 0.7500
Epoch 132/150
0.8896 - val_loss: 0.6620 - val_acc: 0.7460
Epoch 133/150
0.8901 - val_loss: 0.6644 - val_acc: 0.7530
Epoch 134/150
0.8925 - val_loss: 0.6624 - val_acc: 0.7440
Epoch 135/150
0.8912 - val_loss: 0.6636 - val_acc: 0.7470
Epoch 136/150
30/30 [============= ] - Os 3ms/step - loss: 0.3408 - acc:
0.8945 - val_loss: 0.6634 - val_acc: 0.7510
Epoch 137/150
0.8947 - val_loss: 0.6669 - val_acc: 0.7460
Epoch 138/150
0.8959 - val_loss: 0.6677 - val_acc: 0.7490
Epoch 139/150
0.8976 - val_loss: 0.6731 - val_acc: 0.7430
Epoch 140/150
0.8969 - val_loss: 0.6649 - val_acc: 0.7490
Epoch 141/150
0.8991 - val_loss: 0.6679 - val_acc: 0.7510
Epoch 142/150
30/30 [============ ] - Os 3ms/step - loss: 0.3275 - acc:
0.9008 - val_loss: 0.6673 - val_acc: 0.7510
```

```
Epoch 143/150
0.9008 - val_loss: 0.6690 - val_acc: 0.7490
Epoch 144/150
0.9011 - val_loss: 0.6724 - val_acc: 0.7540
Epoch 145/150
0.9032 - val_loss: 0.6680 - val_acc: 0.7500
Epoch 146/150
0.9035 - val_loss: 0.6727 - val_acc: 0.7500
Epoch 147/150
0.9037 - val_loss: 0.6710 - val_acc: 0.7500
Epoch 148/150
0.9055 - val_loss: 0.6789 - val_acc: 0.7460
Epoch 149/150
0.9053 - val_loss: 0.6690 - val_acc: 0.7540
Epoch 150/150
0.9081 - val_loss: 0.6763 - val_acc: 0.7480
```

1.10.3 Model Performance

The attribute .history (stored as a dictionary) contains four entries now: one per metric that was being monitored during training and validation. Print the keys of this dictionary for confirmation:

```
[12]: # Access the history attribute and store the dictionary
baseline_model_val_dict = baseline_model_val.history

# Print the keys
baseline_model_val_dict.keys()
```

```
[12]: dict_keys(['loss', 'acc', 'val_loss', 'val_acc'])
```

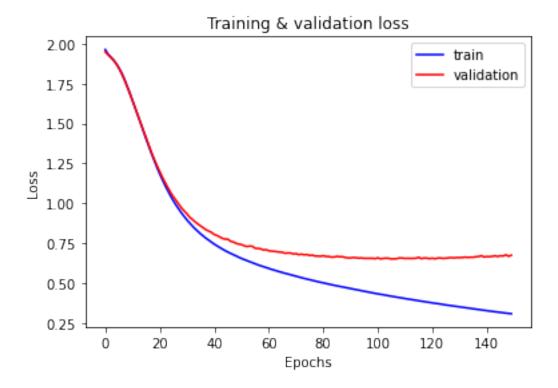
Evaluate this model on the training data:

Training Loss: 0.307
Training Accuracy: 0.905

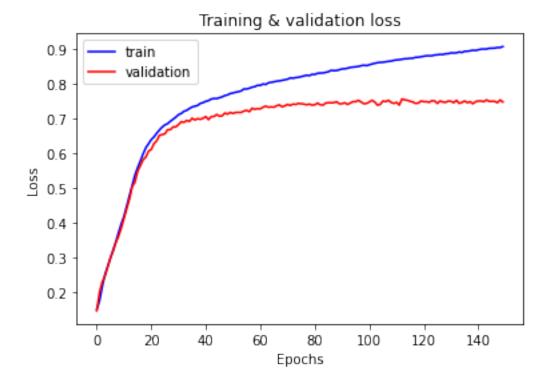
Evaluate this model on the test data:

1.10.4 Plot the Results

Plot the loss versus the number of epochs. Be sure to include the training and the validation loss in the same plot.



Create a second plot comparing training and validation accuracy to the number of epochs.



Did you notice an interesting pattern here? Although the training accuracy keeps increasing when going through more epochs, and the training loss keeps decreasing, the validation accuracy and loss don't necessarily do the same. After a certain point, validation accuracy keeps swinging, which means that you're probably **overfitting** the model to the training data when you train for many epochs past a certain dropoff point. Let's tackle this now. You will now specify an early stopping point when training your model.

1.11 Early Stopping

Overfitting neural networks is something you **want** to avoid at all costs. However, it's not possible to know in advance how many *epochs* you need to train your model on, and running the model multiple times with varying number of *epochs* maybe helpful, but is a time-consuming process.

We've defined a model with the same architecture as above. This time specify an early stopping point when training the model.

- Import EarlyStopping and ModelCheckpoint from keras.callbacks
- Define a list, early_stopping:
 - Monitor 'val_loss' and continue training for 10 epochs before stopping
 - Save the best model while monitoring 'val_loss'

If you need help, consult documentation.

Train model_2. Make sure you set the callbacks argument to early_stopping.

```
Epoch 1/150
60/60 [============= ] - Os 2ms/step - loss: 0.3343 - acc:
0.9009 - val_loss: 0.6802 - val_acc: 0.7370
Epoch 2/150
0.9013 - val_loss: 0.6816 - val_acc: 0.7380
Epoch 3/150
60/60 [============= ] - Os 2ms/step - loss: 0.3258 - acc:
0.9043 - val_loss: 0.6811 - val_acc: 0.7350
Epoch 4/150
0.9045 - val_loss: 0.6859 - val_acc: 0.7400
Epoch 5/150
0.9079 - val_loss: 0.6855 - val_acc: 0.7360
Epoch 6/150
0.9071 - val_loss: 0.6809 - val_acc: 0.7450
Epoch 7/150
0.9101 - val_loss: 0.6828 - val_acc: 0.7470
Epoch 8/150
0.9125 - val_loss: 0.6878 - val_acc: 0.7390
```

```
[23]: # Load the best (saved) model
saved_model = models.load_model('best_model.h5')
```

Now, use this model to to calculate the training and test accuracy:

Nicely done! Did you notice that the model didn't train for all 150 epochs? You reduced your training time.

Now, take a look at how regularization techniques can further improve your model performance.

1.12 L2 Regularization

First, take a look at L2 regularization. Keras makes L2 regularization easy. Simply add the kernel_regularizer=keras.regularizers.12(lambda_coeff) parameter to any model layer. The lambda_coeff parameter determines the strength of the regularization you wish to perform.

• Use 2 hidden layers with 50 units in the first and 25 in the second layer, both with 'relu' activation functions

Add L2 regularization to both the hidden layers with 0.005 as the lambda_coeff

```
[26]: # Import regularizers
    from keras import regularizers
    random.seed(123)
    L2_model = models.Sequential()
    lambda_coeff = 0.005
    # Add the input and first hidden layer
    L2_model.add(layers.Dense(50,
                        kernel_regularizer=regularizers.12(lambda_coeff),
                        activation = "relu",
                        input\_shape = (2000,))
    # Add another hidden layer
    L2_model.add(layers.Dense(25,
                        kernel_regularizer=regularizers.12(lambda_coeff),
                        activation = "relu"))
    # Add an output layer
    L2_model.add(layers.Dense(7, activation='softmax'))
    # Compile the model
    L2_model.compile(optimizer='SGD',
                 loss='categorical_crossentropy',
                 metrics=['acc'])
    # Train the model
    L2_model_val = L2_model.fit(X_train_tokens,
                          y_train_lb,
                          epochs=150,
                          batch_size=256,
                          validation_data=(X_val_tokens, y_val_lb))
    Epoch 1/150
    0.1772 - val_loss: 2.5725 - val_acc: 0.1910
    Epoch 2/150
    0.1991 - val_loss: 2.5500 - val_acc: 0.2160
    Epoch 3/150
    0.2216 - val_loss: 2.5269 - val_acc: 0.2310
    Epoch 4/150
```

0.2479 - val_loss: 2.4997 - val_acc: 0.2450

```
Epoch 5/150
0.2836 - val_loss: 2.4668 - val_acc: 0.2890
Epoch 6/150
0.3255 - val_loss: 2.4269 - val_acc: 0.3280
Epoch 7/150
0.3668 - val_loss: 2.3824 - val_acc: 0.3670
Epoch 8/150
0.4000 - val_loss: 2.3329 - val_acc: 0.3990
Epoch 9/150
30/30 [============= ] - Os 3ms/step - loss: 2.2796 - acc:
0.4309 - val_loss: 2.2812 - val_acc: 0.4190
Epoch 10/150
0.4603 - val_loss: 2.2280 - val_acc: 0.4450
Epoch 11/150
0.4873 - val_loss: 2.1761 - val_acc: 0.4520
Epoch 12/150
0.5108 - val_loss: 2.1258 - val_acc: 0.4750
Epoch 13/150
0.5339 - val_loss: 2.0755 - val_acc: 0.4910
Epoch 14/150
0.5523 - val_loss: 2.0283 - val_acc: 0.5190
Epoch 15/150
0.5713 - val_loss: 1.9841 - val_acc: 0.5330
Epoch 16/150
0.5893 - val_loss: 1.9445 - val_acc: 0.5450
Epoch 17/150
0.6028 - val_loss: 1.9041 - val_acc: 0.5490
Epoch 18/150
0.6163 - val_loss: 1.8653 - val_acc: 0.5770
Epoch 19/150
0.6296 - val_loss: 1.8317 - val_acc: 0.5880
Epoch 20/150
30/30 [============= ] - Os 3ms/step - loss: 1.7714 - acc:
0.6396 - val_loss: 1.7978 - val_acc: 0.6050
```

```
Epoch 21/150
30/30 [============= ] - Os 3ms/step - loss: 1.7380 - acc:
0.6492 - val_loss: 1.7721 - val_acc: 0.6030
Epoch 22/150
0.6564 - val_loss: 1.7395 - val_acc: 0.6100
Epoch 23/150
0.6699 - val_loss: 1.7116 - val_acc: 0.6300
Epoch 24/150
0.6761 - val_loss: 1.6821 - val_acc: 0.6390
Epoch 25/150
0.6865 - val_loss: 1.6561 - val_acc: 0.6450
Epoch 26/150
0.6933 - val_loss: 1.6335 - val_acc: 0.6500
Epoch 27/150
0.7000 - val_loss: 1.6109 - val_acc: 0.6570
Epoch 28/150
0.7065 - val_loss: 1.5922 - val_acc: 0.6570
Epoch 29/150
0.7111 - val_loss: 1.5693 - val_acc: 0.6530
Epoch 30/150
0.7157 - val_loss: 1.5495 - val_acc: 0.6620
Epoch 31/150
0.7196 - val_loss: 1.5395 - val_acc: 0.6770
Epoch 32/150
0.7236 - val_loss: 1.5153 - val_acc: 0.6770
Epoch 33/150
0.7281 - val_loss: 1.4953 - val_acc: 0.6850
Epoch 34/150
0.7312 - val_loss: 1.4807 - val_acc: 0.6850
0.7349 - val_loss: 1.4661 - val_acc: 0.6900
Epoch 36/150
0.7399 - val_loss: 1.4520 - val_acc: 0.7000
```

```
Epoch 37/150
0.7413 - val_loss: 1.4404 - val_acc: 0.7000
Epoch 38/150
0.7447 - val_loss: 1.4270 - val_acc: 0.6890
Epoch 39/150
0.7485 - val_loss: 1.4137 - val_acc: 0.7070
Epoch 40/150
0.7503 - val_loss: 1.4020 - val_acc: 0.7030
Epoch 41/150
0.7556 - val_loss: 1.3930 - val_acc: 0.7120
Epoch 42/150
0.7569 - val_loss: 1.3808 - val_acc: 0.7090
Epoch 43/150
0.7603 - val_loss: 1.3725 - val_acc: 0.7140
Epoch 44/150
0.7651 - val_loss: 1.3712 - val_acc: 0.7070
Epoch 45/150
0.7655 - val_loss: 1.3560 - val_acc: 0.7130
Epoch 46/150
0.7687 - val_loss: 1.3453 - val_acc: 0.7050
Epoch 47/150
0.7716 - val_loss: 1.3388 - val_acc: 0.7070
Epoch 48/150
0.7737 - val_loss: 1.3289 - val_acc: 0.7160
Epoch 49/150
0.7765 - val_loss: 1.3233 - val_acc: 0.7110
Epoch 50/150
0.7800 - val_loss: 1.3146 - val_acc: 0.7120
30/30 [============= ] - Os 3ms/step - loss: 1.2060 - acc:
0.7829 - val_loss: 1.3057 - val_acc: 0.7130
Epoch 52/150
0.7819 - val_loss: 1.2999 - val_acc: 0.7150
```

```
Epoch 53/150
0.7869 - val_loss: 1.2940 - val_acc: 0.7170
Epoch 54/150
0.7885 - val_loss: 1.2903 - val_acc: 0.7080
Epoch 55/150
0.7915 - val_loss: 1.2826 - val_acc: 0.7190
Epoch 56/150
0.7933 - val_loss: 1.2822 - val_acc: 0.7190
Epoch 57/150
0.7936 - val_loss: 1.2820 - val_acc: 0.7220
Epoch 58/150
30/30 [============= ] - Os 3ms/step - loss: 1.1504 - acc:
0.7963 - val_loss: 1.2673 - val_acc: 0.7170
Epoch 59/150
0.7980 - val_loss: 1.2628 - val_acc: 0.7140
Epoch 60/150
0.7993 - val_loss: 1.2579 - val_acc: 0.7210
Epoch 61/150
0.8012 - val_loss: 1.2572 - val_acc: 0.7170
Epoch 62/150
0.8021 - val_loss: 1.2481 - val_acc: 0.7190
Epoch 63/150
0.8027 - val_loss: 1.2436 - val_acc: 0.7210
Epoch 64/150
0.8041 - val_loss: 1.2423 - val_acc: 0.7220
Epoch 65/150
0.8059 - val_loss: 1.2354 - val_acc: 0.7260
Epoch 66/150
0.8087 - val_loss: 1.2363 - val_acc: 0.7230
Epoch 67/150
30/30 [============= ] - Os 3ms/step - loss: 1.0902 - acc:
0.8085 - val_loss: 1.2365 - val_acc: 0.7230
Epoch 68/150
30/30 [============= ] - Os 3ms/step - loss: 1.0844 - acc:
0.8124 - val_loss: 1.2263 - val_acc: 0.7280
```

```
Epoch 69/150
0.8121 - val_loss: 1.2183 - val_acc: 0.7260
Epoch 70/150
0.8155 - val_loss: 1.2176 - val_acc: 0.7270
Epoch 71/150
0.8168 - val_loss: 1.2143 - val_acc: 0.7260
Epoch 72/150
0.8161 - val_loss: 1.2108 - val_acc: 0.7320
Epoch 73/150
0.8204 - val_loss: 1.2088 - val_acc: 0.7270
Epoch 74/150
30/30 [============= ] - Os 3ms/step - loss: 1.0502 - acc:
0.8217 - val_loss: 1.2061 - val_acc: 0.7330
Epoch 75/150
0.8213 - val_loss: 1.2000 - val_acc: 0.7290
Epoch 76/150
0.8233 - val_loss: 1.1990 - val_acc: 0.7300
Epoch 77/150
0.8245 - val_loss: 1.1945 - val_acc: 0.7290
Epoch 78/150
30/30 [============= ] - Os 3ms/step - loss: 1.0288 - acc:
0.8259 - val_loss: 1.1946 - val_acc: 0.7310
Epoch 79/150
30/30 [============= ] - Os 3ms/step - loss: 1.0237 - acc:
0.8265 - val_loss: 1.1880 - val_acc: 0.7270
Epoch 80/150
0.8308 - val_loss: 1.1863 - val_acc: 0.7290
Epoch 81/150
0.8303 - val_loss: 1.1838 - val_acc: 0.7310
Epoch 82/150
0.8321 - val_loss: 1.1835 - val_acc: 0.7290
Epoch 83/150
30/30 [============= ] - Os 3ms/step - loss: 1.0041 - acc:
0.8313 - val_loss: 1.1765 - val_acc: 0.7280
Epoch 84/150
0.8347 - val_loss: 1.1786 - val_acc: 0.7270
```

```
Epoch 85/150
0.8348 - val_loss: 1.1759 - val_acc: 0.7290
Epoch 86/150
0.8364 - val_loss: 1.1720 - val_acc: 0.7250
Epoch 87/150
0.8388 - val_loss: 1.1669 - val_acc: 0.7290
Epoch 88/150
0.8401 - val_loss: 1.1681 - val_acc: 0.7320
Epoch 89/150
0.8415 - val_loss: 1.1630 - val_acc: 0.7290
Epoch 90/150
30/30 [============= ] - Os 3ms/step - loss: 0.9702 - acc:
0.8415 - val_loss: 1.1578 - val_acc: 0.7290
Epoch 91/150
0.8429 - val_loss: 1.1561 - val_acc: 0.7320
Epoch 92/150
0.8448 - val_loss: 1.1534 - val_acc: 0.7270
Epoch 93/150
0.8468 - val_loss: 1.1545 - val_acc: 0.7310
Epoch 94/150
30/30 [============= ] - Os 3ms/step - loss: 0.9534 - acc:
0.8471 - val_loss: 1.1513 - val_acc: 0.7310
Epoch 95/150
30/30 [============= ] - Os 3ms/step - loss: 0.9490 - acc:
0.8476 - val_loss: 1.1532 - val_acc: 0.7280
Epoch 96/150
0.8495 - val_loss: 1.1502 - val_acc: 0.7280
Epoch 97/150
0.8504 - val_loss: 1.1523 - val_acc: 0.7310
Epoch 98/150
0.8491 - val_loss: 1.1421 - val_acc: 0.7330
0.8528 - val_loss: 1.1419 - val_acc: 0.7300
Epoch 100/150
0.8535 - val_loss: 1.1453 - val_acc: 0.7340
```

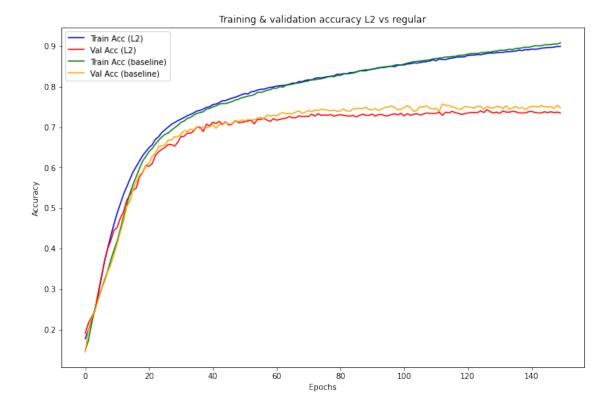
```
Epoch 101/150
0.8536 - val_loss: 1.1396 - val_acc: 0.7280
Epoch 102/150
0.8560 - val_loss: 1.1360 - val_acc: 0.7330
Epoch 103/150
0.8565 - val_loss: 1.1329 - val_acc: 0.7290
Epoch 104/150
0.8587 - val_loss: 1.1291 - val_acc: 0.7320
Epoch 105/150
30/30 [============= ] - Os 3ms/step - loss: 0.9078 - acc:
0.8580 - val_loss: 1.1311 - val_acc: 0.7330
Epoch 106/150
30/30 [============= ] - Os 3ms/step - loss: 0.9039 - acc:
0.8596 - val_loss: 1.1262 - val_acc: 0.7300
Epoch 107/150
0.8612 - val_loss: 1.1255 - val_acc: 0.7320
Epoch 108/150
0.8617 - val_loss: 1.1201 - val_acc: 0.7350
Epoch 109/150
0.8632 - val_loss: 1.1201 - val_acc: 0.7340
Epoch 110/150
30/30 [============= ] - Os 3ms/step - loss: 0.8888 - acc:
0.8664 - val_loss: 1.1219 - val_acc: 0.7340
Epoch 111/150
0.8639 - val_loss: 1.1226 - val_acc: 0.7340
Epoch 112/150
0.8681 - val_loss: 1.1143 - val_acc: 0.7370
Epoch 113/150
0.8671 - val_loss: 1.1225 - val_acc: 0.7290
Epoch 114/150
0.8667 - val_loss: 1.1171 - val_acc: 0.7370
Epoch 115/150
30/30 [============= ] - Os 3ms/step - loss: 0.8700 - acc:
0.8693 - val_loss: 1.1120 - val_acc: 0.7350
Epoch 116/150
0.8705 - val_loss: 1.1096 - val_acc: 0.7390
```

```
Epoch 117/150
0.8720 - val_loss: 1.1090 - val_acc: 0.7360
Epoch 118/150
0.8732 - val_loss: 1.1054 - val_acc: 0.7340
Epoch 119/150
0.8731 - val_loss: 1.1178 - val_acc: 0.7310
Epoch 120/150
0.8737 - val_loss: 1.1053 - val_acc: 0.7330
Epoch 121/150
0.8773 - val_loss: 1.1026 - val_acc: 0.7350
Epoch 122/150
0.8776 - val_loss: 1.1096 - val_acc: 0.7360
Epoch 123/150
0.8780 - val_loss: 1.0963 - val_acc: 0.7360
Epoch 124/150
0.8795 - val_loss: 1.0970 - val_acc: 0.7360
Epoch 125/150
0.8788 - val_loss: 1.0949 - val_acc: 0.7400
Epoch 126/150
30/30 [============= ] - Os 3ms/step - loss: 0.8321 - acc:
0.8804 - val_loss: 1.0927 - val_acc: 0.7360
Epoch 127/150
0.8820 - val_loss: 1.0959 - val_acc: 0.7430
Epoch 128/150
0.8831 - val_loss: 1.0938 - val_acc: 0.7380
Epoch 129/150
0.8828 - val_loss: 1.0914 - val_acc: 0.7350
Epoch 130/150
0.8839 - val_loss: 1.0906 - val_acc: 0.7370
Epoch 131/150
0.8848 - val_loss: 1.0870 - val_acc: 0.7340
Epoch 132/150
0.8848 - val_loss: 1.0922 - val_acc: 0.7400
```

```
Epoch 133/150
0.8860 - val_loss: 1.0872 - val_acc: 0.7370
Epoch 134/150
0.8864 - val_loss: 1.0852 - val_acc: 0.7370
Epoch 135/150
0.8872 - val_loss: 1.0899 - val_acc: 0.7390
Epoch 136/150
0.8880 - val_loss: 1.0829 - val_acc: 0.7380
Epoch 137/150
0.8903 - val_loss: 1.0816 - val_acc: 0.7350
Epoch 138/150
0.8889 - val_loss: 1.0774 - val_acc: 0.7350
Epoch 139/150
0.8916 - val_loss: 1.0850 - val_acc: 0.7350
Epoch 140/150
0.8908 - val_loss: 1.0764 - val_acc: 0.7380
Epoch 141/150
0.8928 - val_loss: 1.0820 - val_acc: 0.7390
Epoch 142/150
30/30 [============= ] - Os 3ms/step - loss: 0.7825 - acc:
0.8923 - val_loss: 1.0753 - val_acc: 0.7360
Epoch 143/150
30/30 [============= ] - Os 3ms/step - loss: 0.7799 - acc:
0.8932 - val_loss: 1.0736 - val_acc: 0.7350
Epoch 144/150
0.8949 - val_loss: 1.0715 - val_acc: 0.7350
Epoch 145/150
0.8959 - val_loss: 1.0718 - val_acc: 0.7380
Epoch 146/150
0.8965 - val_loss: 1.0703 - val_acc: 0.7360
Epoch 147/150
0.8967 - val_loss: 1.0676 - val_acc: 0.7380
Epoch 148/150
30/30 [============= ] - Os 3ms/step - loss: 0.7651 - acc:
0.8976 - val_loss: 1.0709 - val_acc: 0.7360
```

Now, look at the training as well as the validation accuracy for both the L2 and the baseline models.

```
[39]: # L2 model details
      L2_model_dict = L2_model_val.history
      L2 acc values = L2 model dict['acc']
      L2_val_acc_values = L2_model_dict['val_acc']
      # Baseline model
      baseline model acc = baseline model val dict['acc']
      baseline_model_val_acc = baseline_model_val_dict['val_acc']
      fig, ax = plt.subplots(figsize=(12, 8))
      plt.plot(L2_acc_values, color = "blue", label = "Train Acc (L2)")
      plt.plot(L2_val_acc_values, color = "red", label = "Val Acc (L2)")
      plt.plot(baseline_model_acc, color = "green", label = "Train Acc (baseline)")
      plt.plot(baseline model val acc, color = "orange", label = "Val Acc (baseline)")
      ax.set title('Training & validation accuracy L2 vs regular')
      ax.set_xlabel('Epochs')
      ax.set_ylabel('Accuracy')
      plt.legend();
      # Plot the accuracy for these models
      # fig, ax = plt.subplots(figsize=(12, 8))
      # epochs = range(1, len(acc_values) + 1)
      # ax.plot(epochs, L2_acc_values, label='Training acc L2')
      # ax.plot(epochs, L2_val_acc_values, label='Validation acc L2')
      # ax.plot(epochs, baseline_model_acc, label='Training acc')
      # ax.plot(epochs, baseline model_val_acc, label='Validation acc')
      # ax.set_title('Training & validation accuracy L2 vs regular')
      # ax.set xlabel('Epochs')
      # ax.set_ylabel('Accuracy')
      # ax.legend();
```



The results of L2 regularization are quite disappointing here. Notice the discrepancy between validation and training accuracy seems to have decreased slightly, but the end result is definitely not getting better.

1.13 L1 Regularization

Now have a look at L1 regularization. Will this work better?

- Use 2 hidden layers with 50 units in the first and 25 in the second layer, both with 'relu' activation functions
- Add L1 regularization to both the hidden layers with 0.005 as the lambda_coeff

```
kernel_regularizer=regularizers.l1(lambda_coeff),
                  activation = "relu"))
# Add an output layer
L1_model.add(layers.Dense(7, activation='softmax'))
# Compile the model
L1_model.compile(optimizer='SGD',
            loss='categorical_crossentropy',
            metrics=['acc'])
# Train the model
L1_model_val = L1_model.fit(X_train_tokens,
                    y_train_lb,
                    epochs=150,
                    batch_size=256,
                    validation_data=(X_val_tokens, y_val_lb))
Epoch 1/150
30/30 [============== ] - Os 8ms/step - loss: 15.9841 - acc:
0.1525 - val_loss: 15.5799 - val_acc: 0.1660
Epoch 2/150
0.1759 - val_loss: 14.8352 - val_acc: 0.1820
Epoch 3/150
0.2048 - val_loss: 14.1141 - val_acc: 0.2070
Epoch 4/150
0.2312 - val_loss: 13.4143 - val_acc: 0.2360
Epoch 5/150
0.2572 - val_loss: 12.7343 - val_acc: 0.2560
Epoch 6/150
30/30 [============== ] - Os 3ms/step - loss: 12.4138 - acc:
0.2821 - val_loss: 12.0733 - val_acc: 0.2780
Epoch 7/150
30/30 [============== ] - Os 3ms/step - loss: 11.7611 - acc:
0.3108 - val_loss: 11.4308 - val_acc: 0.3070
Epoch 8/150
0.3384 - val_loss: 10.8063 - val_acc: 0.3400
Epoch 9/150
30/30 [============== ] - Os 3ms/step - loss: 10.5125 - acc:
0.3729 - val_loss: 10.2028 - val_acc: 0.3790
Epoch 10/150
```

```
0.4088 - val_loss: 9.6201 - val_acc: 0.3920
Epoch 11/150
0.4320 - val_loss: 9.0583 - val_acc: 0.4230
Epoch 12/150
0.4585 - val_loss: 8.5183 - val_acc: 0.4340
Epoch 13/150
0.4791 - val_loss: 7.9998 - val_acc: 0.4570
Epoch 14/150
0.5035 - val_loss: 7.5047 - val_acc: 0.4720
Epoch 15/150
0.5173 - val_loss: 7.0306 - val_acc: 0.4960
Epoch 16/150
0.5439 - val_loss: 6.5801 - val_acc: 0.5090
Epoch 17/150
0.5517 - val_loss: 6.1489 - val_acc: 0.5430
Epoch 18/150
0.5667 - val_loss: 5.7408 - val_acc: 0.5260
Epoch 19/150
0.5727 - val_loss: 5.3530 - val_acc: 0.5630
Epoch 20/150
0.5855 - val_loss: 4.9877 - val_acc: 0.5710
Epoch 21/150
0.5907 - val_loss: 4.6466 - val_acc: 0.5790
Epoch 22/150
0.6013 - val_loss: 4.3270 - val_acc: 0.6010
Epoch 23/150
0.6119 - val_loss: 4.0291 - val_acc: 0.6120
Epoch 24/150
0.6160 - val_loss: 3.7535 - val_acc: 0.6140
Epoch 25/150
0.6220 - val_loss: 3.5026 - val_acc: 0.6020
Epoch 26/150
```

```
0.6232 - val_loss: 3.2703 - val_acc: 0.6280
Epoch 27/150
0.6316 - val_loss: 3.0624 - val_acc: 0.6370
Epoch 28/150
0.6349 - val_loss: 2.8751 - val_acc: 0.6390
Epoch 29/150
0.6405 - val_loss: 2.7092 - val_acc: 0.6380
Epoch 30/150
0.6393 - val_loss: 2.5663 - val_acc: 0.6380
Epoch 31/150
0.6432 - val_loss: 2.4400 - val_acc: 0.6510
Epoch 32/150
0.6456 - val_loss: 2.3365 - val_acc: 0.6420
Epoch 33/150
0.6469 - val_loss: 2.2505 - val_acc: 0.6430
Epoch 34/150
0.6501 - val_loss: 2.1828 - val_acc: 0.6470
Epoch 35/150
0.6549 - val_loss: 2.1320 - val_acc: 0.6470
0.6543 - val_loss: 2.0935 - val_acc: 0.6490
Epoch 37/150
0.6559 - val_loss: 2.0631 - val_acc: 0.6540
Epoch 38/150
0.6576 - val_loss: 2.0383 - val_acc: 0.6580
Epoch 39/150
0.6631 - val_loss: 2.0169 - val_acc: 0.6520
Epoch 40/150
0.6611 - val_loss: 1.9951 - val_acc: 0.6590
Epoch 41/150
0.6639 - val_loss: 1.9786 - val_acc: 0.6550
Epoch 42/150
```

```
0.6660 - val_loss: 1.9594 - val_acc: 0.6560
Epoch 43/150
0.6675 - val_loss: 1.9434 - val_acc: 0.6580
Epoch 44/150
0.6675 - val_loss: 1.9265 - val_acc: 0.6630
Epoch 45/150
0.6679 - val_loss: 1.9104 - val_acc: 0.6680
Epoch 46/150
0.6716 - val_loss: 1.8959 - val_acc: 0.6710
Epoch 47/150
0.6728 - val_loss: 1.8833 - val_acc: 0.6710
Epoch 48/150
0.6743 - val_loss: 1.8733 - val_acc: 0.6640
Epoch 49/150
0.6721 - val_loss: 1.8590 - val_acc: 0.6720
Epoch 50/150
0.6741 - val_loss: 1.8431 - val_acc: 0.6690
Epoch 51/150
0.6763 - val_loss: 1.8321 - val_acc: 0.6720
Epoch 52/150
0.6777 - val_loss: 1.8180 - val_acc: 0.6700
Epoch 53/150
0.6783 - val_loss: 1.8089 - val_acc: 0.6730
Epoch 54/150
0.6787 - val_loss: 1.7982 - val_acc: 0.6740
Epoch 55/150
0.6807 - val_loss: 1.7858 - val_acc: 0.6740
Epoch 56/150
0.6816 - val_loss: 1.7757 - val_acc: 0.6730
Epoch 57/150
0.6832 - val_loss: 1.7693 - val_acc: 0.6720
Epoch 58/150
```

```
0.6821 - val_loss: 1.7583 - val_acc: 0.6760
Epoch 59/150
0.6840 - val_loss: 1.7457 - val_acc: 0.6790
Epoch 60/150
0.6841 - val_loss: 1.7401 - val_acc: 0.6770
Epoch 61/150
0.6847 - val_loss: 1.7255 - val_acc: 0.6790
Epoch 62/150
0.6863 - val_loss: 1.7167 - val_acc: 0.6780
Epoch 63/150
0.6864 - val_loss: 1.7086 - val_acc: 0.6800
Epoch 64/150
0.6852 - val_loss: 1.7001 - val_acc: 0.6750
Epoch 65/150
0.6856 - val_loss: 1.6954 - val_acc: 0.6780
Epoch 66/150
0.6873 - val_loss: 1.6831 - val_acc: 0.6830
Epoch 67/150
0.6875 - val_loss: 1.6734 - val_acc: 0.6780
0.6873 - val_loss: 1.6685 - val_acc: 0.6840
Epoch 69/150
0.6879 - val_loss: 1.6574 - val_acc: 0.6830
Epoch 70/150
0.6889 - val_loss: 1.6538 - val_acc: 0.6780
Epoch 71/150
0.6899 - val_loss: 1.6419 - val_acc: 0.6810
Epoch 72/150
0.6897 - val_loss: 1.6347 - val_acc: 0.6780
Epoch 73/150
0.6912 - val_loss: 1.6336 - val_acc: 0.6750
Epoch 74/150
```

```
0.6909 - val_loss: 1.6210 - val_acc: 0.6810
Epoch 75/150
0.6911 - val_loss: 1.6159 - val_acc: 0.6760
Epoch 76/150
0.6917 - val_loss: 1.6093 - val_acc: 0.6830
Epoch 77/150
0.6925 - val_loss: 1.6044 - val_acc: 0.6860
Epoch 78/150
0.6944 - val_loss: 1.5922 - val_acc: 0.6820
Epoch 79/150
0.6933 - val_loss: 1.5859 - val_acc: 0.6850
Epoch 80/150
0.6935 - val_loss: 1.5763 - val_acc: 0.6790
Epoch 81/150
0.6929 - val_loss: 1.5724 - val_acc: 0.6790
Epoch 82/150
0.6952 - val_loss: 1.5645 - val_acc: 0.6890
Epoch 83/150
0.6957 - val_loss: 1.5569 - val_acc: 0.6830
0.6933 - val_loss: 1.5531 - val_acc: 0.6850
Epoch 85/150
0.6963 - val_loss: 1.5446 - val_acc: 0.6810
Epoch 86/150
0.6969 - val_loss: 1.5382 - val_acc: 0.6870
Epoch 87/150
0.6963 - val_loss: 1.5311 - val_acc: 0.6850
Epoch 88/150
0.6960 - val_loss: 1.5243 - val_acc: 0.6850
Epoch 89/150
0.6969 - val_loss: 1.5197 - val_acc: 0.6830
Epoch 90/150
```

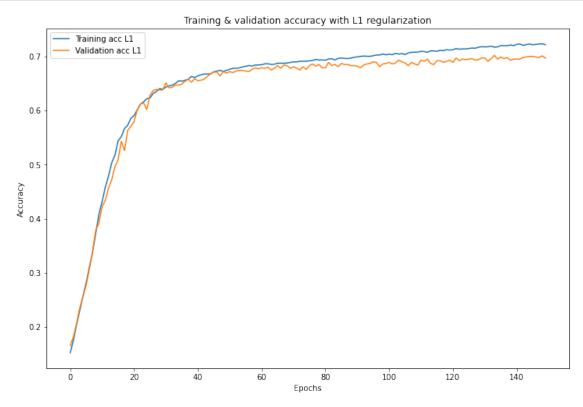
```
0.6984 - val_loss: 1.5133 - val_acc: 0.6830
Epoch 91/150
0.6991 - val_loss: 1.5084 - val_acc: 0.6820
Epoch 92/150
0.7000 - val_loss: 1.5025 - val_acc: 0.6790
Epoch 93/150
0.7007 - val_loss: 1.4947 - val_acc: 0.6840
Epoch 94/150
0.7003 - val_loss: 1.4887 - val_acc: 0.6860
Epoch 95/150
0.7001 - val_loss: 1.4834 - val_acc: 0.6870
Epoch 96/150
0.7013 - val_loss: 1.4777 - val_acc: 0.6900
Epoch 97/150
0.7025 - val_loss: 1.4724 - val_acc: 0.6890
Epoch 98/150
0.7027 - val_loss: 1.4711 - val_acc: 0.6810
Epoch 99/150
0.7044 - val_loss: 1.4599 - val_acc: 0.6860
Epoch 100/150
0.7031 - val_loss: 1.4585 - val_acc: 0.6870
Epoch 101/150
0.7041 - val_loss: 1.4515 - val_acc: 0.6890
Epoch 102/150
0.7032 - val_loss: 1.4441 - val_acc: 0.6860
Epoch 103/150
0.7055 - val_loss: 1.4392 - val_acc: 0.6880
Epoch 104/150
30/30 [============= ] - Os 3ms/step - loss: 1.4210 - acc:
0.7043 - val_loss: 1.4367 - val_acc: 0.6930
Epoch 105/150
0.7052 - val_loss: 1.4278 - val_acc: 0.6900
Epoch 106/150
```

```
0.7035 - val_loss: 1.4228 - val_acc: 0.6880
Epoch 107/150
0.7063 - val_loss: 1.4192 - val_acc: 0.6830
Epoch 108/150
0.7076 - val_loss: 1.4144 - val_acc: 0.6890
Epoch 109/150
0.7077 - val_loss: 1.4093 - val_acc: 0.6860
Epoch 110/150
0.7081 - val_loss: 1.4103 - val_acc: 0.6840
Epoch 111/150
0.7093 - val_loss: 1.3999 - val_acc: 0.6930
Epoch 112/150
0.7091 - val_loss: 1.3936 - val_acc: 0.6910
Epoch 113/150
0.7076 - val_loss: 1.3882 - val_acc: 0.6950
Epoch 114/150
0.7104 - val_loss: 1.3875 - val_acc: 0.6870
Epoch 115/150
0.7099 - val_loss: 1.3840 - val_acc: 0.6850
Epoch 116/150
0.7095 - val_loss: 1.3776 - val_acc: 0.6920
Epoch 117/150
0.7113 - val_loss: 1.3766 - val_acc: 0.6920
Epoch 118/150
0.7105 - val_loss: 1.3705 - val_acc: 0.6890
Epoch 119/150
0.7124 - val_loss: 1.3640 - val_acc: 0.6910
Epoch 120/150
0.7117 - val_loss: 1.3561 - val_acc: 0.6930
Epoch 121/150
0.7124 - val_loss: 1.3519 - val_acc: 0.6890
Epoch 122/150
```

```
0.7145 - val_loss: 1.3507 - val_acc: 0.6970
Epoch 123/150
0.7133 - val_loss: 1.3465 - val_acc: 0.6920
Epoch 124/150
0.7139 - val_loss: 1.3400 - val_acc: 0.6950
Epoch 125/150
0.7139 - val_loss: 1.3366 - val_acc: 0.6940
Epoch 126/150
0.7145 - val_loss: 1.3324 - val_acc: 0.6950
Epoch 127/150
30/30 [============= ] - Os 3ms/step - loss: 1.3114 - acc:
0.7155 - val_loss: 1.3287 - val_acc: 0.6960
Epoch 128/150
0.7151 - val_loss: 1.3251 - val_acc: 0.6930
Epoch 129/150
0.7169 - val_loss: 1.3209 - val_acc: 0.6940
Epoch 130/150
0.7179 - val_loss: 1.3211 - val_acc: 0.6970
Epoch 131/150
0.7176 - val_loss: 1.3128 - val_acc: 0.6970
Epoch 132/150
0.7179 - val_loss: 1.3137 - val_acc: 0.6910
Epoch 133/150
0.7188 - val_loss: 1.3119 - val_acc: 0.6960
Epoch 134/150
0.7171 - val_loss: 1.3039 - val_acc: 0.7020
Epoch 135/150
0.7176 - val_loss: 1.2972 - val_acc: 0.6950
Epoch 136/150
0.7200 - val_loss: 1.2937 - val_acc: 0.6990
Epoch 137/150
0.7199 - val_loss: 1.2970 - val_acc: 0.6960
Epoch 138/150
```

```
0.7197 - val_loss: 1.2881 - val_acc: 0.6980
   Epoch 139/150
   0.7211 - val_loss: 1.2841 - val_acc: 0.6930
   Epoch 140/150
   0.7199 - val_loss: 1.2855 - val_acc: 0.6950
   Epoch 141/150
   0.7223 - val_loss: 1.2778 - val_acc: 0.6950
   Epoch 142/150
   0.7229 - val_loss: 1.2758 - val_acc: 0.6950
   Epoch 143/150
   0.7204 - val_loss: 1.2692 - val_acc: 0.6980
   Epoch 144/150
   0.7219 - val_loss: 1.2661 - val_acc: 0.6990
   Epoch 145/150
   0.7228 - val_loss: 1.2648 - val_acc: 0.7000
   Epoch 146/150
   0.7216 - val_loss: 1.2601 - val_acc: 0.7000
   Epoch 147/150
   0.7223 - val_loss: 1.2588 - val_acc: 0.6990
   Epoch 148/150
   0.7228 - val_loss: 1.2536 - val_acc: 0.6980
   Epoch 149/150
   30/30 [============= ] - Os 3ms/step - loss: 1.2314 - acc:
   0.7232 - val_loss: 1.2507 - val_acc: 0.7010
   Epoch 150/150
   0.7217 - val loss: 1.2503 - val acc: 0.6970
   Plot the training as well as the validation accuracy for the L1 model:
[41]: fig, ax = plt.subplots(figsize=(12, 8))
   L1_model_dict = L1_model_val.history
   acc_values = L1_model_dict['acc']
   val_acc_values = L1_model_dict['val_acc']
   # epochs = range(1, len(acc_values) + 1)
```

```
ax.plot(acc_values, label='Training acc L1')
ax.plot(val_acc_values, label='Validation acc L1')
ax.set_title('Training & validation accuracy with L1 regularization')
ax.set_xlabel('Epochs')
ax.set_ylabel('Accuracy')
ax.legend();
```



Notice how the training and validation accuracy don't diverge as much as before. Unfortunately, the validation accuracy isn't still that good. Next, experiment with dropout regularization to see if it offers any advantages.

1.14 Dropout Regularization

It's time to try another technique: applying dropout to layers. As discussed in the earlier lesson, this involves setting a certain proportion of units in each layer to zero. In the following cell:

- Apply a dropout rate of 30% to the input layer
- Add a first hidden layer with 50 units and 'relu' activation
- Apply a dropout rate of 30% to the first hidden layer
- Add a second hidden layer with 25 units and 'relu' activation
- Apply a dropout rate of 30% to the second hidden layer

```
[42]: # This cell may take about a minute to run
     random.seed(123)
     dropout_model = models.Sequential()
     # Implement dropout to the input layer
     # NOTE: This is where you define the number of units in the input layer
     dropout_model.add(layers.Dropout(0.3, input_shape = (2000,)))
     # Add the first hidden layer
     dropout_model.add(layers.Dense(50, activation = "relu"))
     # Implement dropout to the first hidden layer
     dropout_model.add(layers.Dropout(0.3))
     # Add the second hidden layer
     dropout_model.add(layers.Dense(25, activation = "relu"))
     # Implement dropout to the second hidden layer
     dropout_model.add(layers.Dropout(0.3))
     # Add the output layer
     dropout_model.add(layers.Dense(7, activation='softmax'))
     # Compile the model
     dropout_model.compile(optimizer='SGD',
                        loss='categorical_crossentropy',
                        metrics=['acc'])
     # Train the model
     dropout_model_val = dropout_model.fit(X_train_tokens,
                                       y_train_lb,
                                       epochs=150,
                                       batch_size=256,
                                       validation_data=(X_val_tokens, y_val_lb))
    Epoch 1/150
    30/30 [============= ] - Os 10ms/step - loss: 1.9750 - acc:
    0.1613 - val_loss: 1.9361 - val_acc: 0.1550
    Epoch 2/150
    0.1675 - val_loss: 1.9274 - val_acc: 0.1750
    Epoch 3/150
    0.1688 - val_loss: 1.9204 - val_acc: 0.1820
    Epoch 4/150
```

```
0.1840 - val_loss: 1.9126 - val_acc: 0.1910
Epoch 5/150
0.1833 - val_loss: 1.9041 - val_acc: 0.1960
Epoch 6/150
0.2045 - val_loss: 1.8946 - val_acc: 0.2020
Epoch 7/150
0.1987 - val_loss: 1.8847 - val_acc: 0.2130
Epoch 8/150
0.2029 - val_loss: 1.8746 - val_acc: 0.2240
Epoch 9/150
0.2155 - val_loss: 1.8618 - val_acc: 0.2310
Epoch 10/150
0.2220 - val_loss: 1.8493 - val_acc: 0.2460
Epoch 11/150
0.2405 - val_loss: 1.8348 - val_acc: 0.2630
Epoch 12/150
0.2417 - val_loss: 1.8198 - val_acc: 0.2800
Epoch 13/150
0.2452 - val_loss: 1.8007 - val_acc: 0.2900
Epoch 14/150
0.2596 - val_loss: 1.7805 - val_acc: 0.3120
Epoch 15/150
0.2631 - val loss: 1.7593 - val acc: 0.3200
Epoch 16/150
0.2757 - val_loss: 1.7374 - val_acc: 0.3290
Epoch 17/150
0.2853 - val_loss: 1.7161 - val_acc: 0.3550
Epoch 18/150
0.3065 - val_loss: 1.6903 - val_acc: 0.3610
Epoch 19/150
0.3095 - val_loss: 1.6662 - val_acc: 0.3940
Epoch 20/150
```

```
0.3217 - val_loss: 1.6403 - val_acc: 0.4220
Epoch 21/150
0.3308 - val_loss: 1.6120 - val_acc: 0.4340
Epoch 22/150
0.3339 - val_loss: 1.5859 - val_acc: 0.4480
Epoch 23/150
0.3453 - val_loss: 1.5582 - val_acc: 0.4680
Epoch 24/150
0.3464 - val_loss: 1.5328 - val_acc: 0.4950
Epoch 25/150
0.3580 - val_loss: 1.5065 - val_acc: 0.5110
Epoch 26/150
0.3801 - val_loss: 1.4802 - val_acc: 0.5290
Epoch 27/150
0.3824 - val_loss: 1.4552 - val_acc: 0.5400
Epoch 28/150
0.4055 - val_loss: 1.4295 - val_acc: 0.5470
Epoch 29/150
0.4039 - val_loss: 1.4052 - val_acc: 0.5570
Epoch 30/150
0.4092 - val_loss: 1.3798 - val_acc: 0.5710
Epoch 31/150
0.4233 - val loss: 1.3570 - val acc: 0.5760
Epoch 32/150
0.4275 - val_loss: 1.3369 - val_acc: 0.5790
Epoch 33/150
0.4427 - val_loss: 1.3152 - val_acc: 0.5970
Epoch 34/150
0.4489 - val_loss: 1.2919 - val_acc: 0.5950
Epoch 35/150
0.4460 - val_loss: 1.2709 - val_acc: 0.6030
Epoch 36/150
```

```
0.4548 - val_loss: 1.2519 - val_acc: 0.6080
Epoch 37/150
0.4572 - val_loss: 1.2358 - val_acc: 0.6220
Epoch 38/150
0.4756 - val_loss: 1.2144 - val_acc: 0.6130
Epoch 39/150
0.4692 - val_loss: 1.2012 - val_acc: 0.6240
Epoch 40/150
0.4840 - val_loss: 1.1854 - val_acc: 0.6280
Epoch 41/150
0.4807 - val_loss: 1.1656 - val_acc: 0.6340
Epoch 42/150
0.4985 - val_loss: 1.1520 - val_acc: 0.6410
Epoch 43/150
0.4976 - val_loss: 1.1352 - val_acc: 0.6470
Epoch 44/150
0.4992 - val_loss: 1.1205 - val_acc: 0.6440
Epoch 45/150
0.4948 - val_loss: 1.1094 - val_acc: 0.6530
Epoch 46/150
0.5019 - val_loss: 1.0997 - val_acc: 0.6580
Epoch 47/150
0.5081 - val_loss: 1.0835 - val_acc: 0.6630
Epoch 48/150
0.5177 - val_loss: 1.0714 - val_acc: 0.6560
Epoch 49/150
0.5163 - val_loss: 1.0576 - val_acc: 0.6700
Epoch 50/150
30/30 [============= ] - Os 5ms/step - loss: 1.2800 - acc:
0.5152 - val_loss: 1.0484 - val_acc: 0.6720
Epoch 51/150
0.5296 - val_loss: 1.0386 - val_acc: 0.6670
Epoch 52/150
```

```
0.5347 - val_loss: 1.0270 - val_acc: 0.6800
Epoch 53/150
0.5383 - val_loss: 1.0151 - val_acc: 0.6770
Epoch 54/150
0.5411 - val_loss: 1.0066 - val_acc: 0.6820
Epoch 55/150
0.5415 - val_loss: 1.0003 - val_acc: 0.6940
Epoch 56/150
0.5443 - val_loss: 0.9896 - val_acc: 0.6880
Epoch 57/150
0.5465 - val_loss: 0.9813 - val_acc: 0.6930
Epoch 58/150
0.5544 - val_loss: 0.9742 - val_acc: 0.6870
Epoch 59/150
0.5571 - val_loss: 0.9649 - val_acc: 0.6930
Epoch 60/150
0.5641 - val_loss: 0.9549 - val_acc: 0.6970
Epoch 61/150
0.5603 - val_loss: 0.9481 - val_acc: 0.6940
Epoch 62/150
0.5653 - val_loss: 0.9421 - val_acc: 0.6920
Epoch 63/150
0.5629 - val loss: 0.9352 - val acc: 0.6990
Epoch 64/150
0.5651 - val_loss: 0.9320 - val_acc: 0.6930
Epoch 65/150
0.5727 - val_loss: 0.9216 - val_acc: 0.6960
Epoch 66/150
0.5688 - val_loss: 0.9172 - val_acc: 0.7020
Epoch 67/150
0.5689 - val_loss: 0.9106 - val_acc: 0.7050
Epoch 68/150
```

```
0.5844 - val_loss: 0.8996 - val_acc: 0.6990
Epoch 69/150
0.5857 - val_loss: 0.8949 - val_acc: 0.7010
Epoch 70/150
0.5809 - val_loss: 0.8906 - val_acc: 0.7060
Epoch 71/150
0.5833 - val_loss: 0.8831 - val_acc: 0.7080
Epoch 72/150
0.5793 - val_loss: 0.8780 - val_acc: 0.7070
Epoch 73/150
0.5800 - val_loss: 0.8737 - val_acc: 0.7070
Epoch 74/150
0.5901 - val_loss: 0.8706 - val_acc: 0.7120
Epoch 75/150
0.5920 - val_loss: 0.8664 - val_acc: 0.7110
Epoch 76/150
0.5891 - val_loss: 0.8626 - val_acc: 0.7080
Epoch 77/150
0.5923 - val_loss: 0.8578 - val_acc: 0.7130
Epoch 78/150
0.5989 - val_loss: 0.8531 - val_acc: 0.7130
Epoch 79/150
0.5987 - val loss: 0.8451 - val acc: 0.7140
Epoch 80/150
0.6003 - val_loss: 0.8406 - val_acc: 0.7130
Epoch 81/150
0.6059 - val_loss: 0.8370 - val_acc: 0.7120
Epoch 82/150
0.6009 - val_loss: 0.8342 - val_acc: 0.7140
Epoch 83/150
0.5983 - val_loss: 0.8303 - val_acc: 0.7140
Epoch 84/150
```

```
0.6069 - val_loss: 0.8239 - val_acc: 0.7150
Epoch 85/150
0.6109 - val_loss: 0.8191 - val_acc: 0.7180
Epoch 86/150
0.6143 - val_loss: 0.8170 - val_acc: 0.7210
Epoch 87/150
0.6137 - val_loss: 0.8109 - val_acc: 0.7210
Epoch 88/150
0.6233 - val_loss: 0.8048 - val_acc: 0.7210
Epoch 89/150
0.6115 - val_loss: 0.7988 - val_acc: 0.7220
Epoch 90/150
0.6172 - val_loss: 0.7984 - val_acc: 0.7180
Epoch 91/150
0.6191 - val_loss: 0.7957 - val_acc: 0.7180
Epoch 92/150
0.6225 - val_loss: 0.7939 - val_acc: 0.7180
Epoch 93/150
0.6163 - val_loss: 0.7880 - val_acc: 0.7220
Epoch 94/150
0.6332 - val_loss: 0.7861 - val_acc: 0.7240
Epoch 95/150
0.6236 - val loss: 0.7833 - val acc: 0.7230
Epoch 96/150
0.6273 - val_loss: 0.7812 - val_acc: 0.7250
Epoch 97/150
0.6300 - val_loss: 0.7784 - val_acc: 0.7250
Epoch 98/150
30/30 [============= ] - Os 5ms/step - loss: 1.0024 - acc:
0.6312 - val_loss: 0.7761 - val_acc: 0.7270
Epoch 99/150
0.6292 - val_loss: 0.7736 - val_acc: 0.7290
Epoch 100/150
```

```
0.6355 - val_loss: 0.7675 - val_acc: 0.7250
Epoch 101/150
0.6376 - val_loss: 0.7651 - val_acc: 0.7260
Epoch 102/150
0.6360 - val_loss: 0.7598 - val_acc: 0.7270
Epoch 103/150
0.6360 - val_loss: 0.7569 - val_acc: 0.7280
Epoch 104/150
0.6425 - val_loss: 0.7548 - val_acc: 0.7290
Epoch 105/150
0.6376 - val_loss: 0.7526 - val_acc: 0.7310
Epoch 106/150
0.6369 - val_loss: 0.7528 - val_acc: 0.7310
Epoch 107/150
0.6437 - val_loss: 0.7508 - val_acc: 0.7300
Epoch 108/150
0.6379 - val_loss: 0.7471 - val_acc: 0.7310
Epoch 109/150
0.6404 - val_loss: 0.7450 - val_acc: 0.7310
Epoch 110/150
0.6465 - val_loss: 0.7415 - val_acc: 0.7320
Epoch 111/150
0.6468 - val loss: 0.7389 - val acc: 0.7320
Epoch 112/150
0.6521 - val_loss: 0.7371 - val_acc: 0.7310
Epoch 113/150
0.6479 - val_loss: 0.7333 - val_acc: 0.7290
Epoch 114/150
0.6444 - val_loss: 0.7347 - val_acc: 0.7330
Epoch 115/150
0.6533 - val_loss: 0.7335 - val_acc: 0.7350
Epoch 116/150
```

```
0.6528 - val_loss: 0.7273 - val_acc: 0.7310
Epoch 117/150
0.6499 - val_loss: 0.7272 - val_acc: 0.7360
Epoch 118/150
0.6563 - val_loss: 0.7250 - val_acc: 0.7330
Epoch 119/150
0.6476 - val_loss: 0.7224 - val_acc: 0.7370
Epoch 120/150
0.6575 - val_loss: 0.7162 - val_acc: 0.7340
Epoch 121/150
0.6549 - val_loss: 0.7173 - val_acc: 0.7340
Epoch 122/150
0.6669 - val_loss: 0.7179 - val_acc: 0.7360
Epoch 123/150
0.6521 - val_loss: 0.7143 - val_acc: 0.7370
Epoch 124/150
0.6639 - val_loss: 0.7139 - val_acc: 0.7380
Epoch 125/150
0.6588 - val_loss: 0.7127 - val_acc: 0.7380
Epoch 126/150
0.6573 - val_loss: 0.7098 - val_acc: 0.7390
Epoch 127/150
0.6572 - val_loss: 0.7057 - val_acc: 0.7370
Epoch 128/150
0.6661 - val_loss: 0.7037 - val_acc: 0.7350
Epoch 129/150
0.6693 - val_loss: 0.7003 - val_acc: 0.7390
Epoch 130/150
0.6613 - val_loss: 0.6974 - val_acc: 0.7390
Epoch 131/150
0.6668 - val_loss: 0.7000 - val_acc: 0.7420
Epoch 132/150
```

```
0.6689 - val_loss: 0.7001 - val_acc: 0.7400
Epoch 133/150
0.6677 - val_loss: 0.6978 - val_acc: 0.7400
Epoch 134/150
0.6691 - val_loss: 0.6967 - val_acc: 0.7450
Epoch 135/150
0.6673 - val_loss: 0.6929 - val_acc: 0.7440
Epoch 136/150
0.6697 - val_loss: 0.6911 - val_acc: 0.7420
Epoch 137/150
0.6696 - val_loss: 0.6892 - val_acc: 0.7390
Epoch 138/150
0.6756 - val_loss: 0.6871 - val_acc: 0.7390
Epoch 139/150
0.6752 - val_loss: 0.6860 - val_acc: 0.7400
Epoch 140/150
0.6777 - val_loss: 0.6829 - val_acc: 0.7430
Epoch 141/150
0.6747 - val_loss: 0.6855 - val_acc: 0.7450
Epoch 142/150
0.6760 - val_loss: 0.6852 - val_acc: 0.7410
Epoch 143/150
0.6804 - val loss: 0.6834 - val acc: 0.7450
Epoch 144/150
0.6749 - val_loss: 0.6795 - val_acc: 0.7460
Epoch 145/150
0.6780 - val_loss: 0.6771 - val_acc: 0.7450
Epoch 146/150
0.6875 - val_loss: 0.6774 - val_acc: 0.7470
Epoch 147/150
0.6864 - val_loss: 0.6759 - val_acc: 0.7450
Epoch 148/150
```

```
0.6815 - val_loss: 0.6757 - val_acc: 0.7470
   Epoch 149/150
   0.6776 - val_loss: 0.6700 - val_acc: 0.7480
   Epoch 150/150
   0.6824 - val_loss: 0.6749 - val_acc: 0.7460
[45]: results_train = dropout_model.evaluate(X_train_tokens, y_train_lb)
   print(f'Training Loss: {results_train[0]:.3} \nTraining Accuracy:

√{results_train[1]:.3}')

   print('----')
   results_test = dropout_model.evaluate(X_test_tokens, y_test_lb)
   print(f'Test Loss: {results_test[0]:.3} \nTest Accuracy: {results_test[1]:.3}')
   Training Loss: 0.57
   Training Accuracy: 0.806
   0.7753
   Test Loss: 0.642
   Test Accuracy: 0.775
```

You can see here that the validation performance has improved again, and the training and test accuracy are very close!

1.15 Bigger Data?

Finally, let's examine if we can improve the model's performance just by adding more data. We've quadrapled the sample dataset from 10,000 to 40,000 observations, and all you need to do is run the code!

```
otest size=6000,
       →random state=42)
      # Validation set
      X_train_final_bigger, X_val_bigger, y_train_final_bigger, y_val_bigger = __
       ⇔train_test_split(X_train_bigger,
                  y_train_bigger,
                  test_size=4000,
                  random_state=42)
      # One-hot encoding of the complaints
      tokenizer = Tokenizer(num_words=2000)
      tokenizer.fit_on_texts(X_train_final_bigger)
      X_train_tokens_bigger = tokenizer.texts_to_matrix(X_train_final_bigger,_u
       →mode='binary')
      X_val_tokens_bigger = tokenizer.texts_to_matrix(X_val_bigger, mode='binary')
      X_test_tokens_bigger = tokenizer.texts_to_matrix(X_test_bigger, mode='binary')
      # One-hot encoding of products
      lb = LabelBinarizer()
      lb.fit(y_train_final_bigger)
      y_train_lb_bigger = to_categorical(lb.transform(y_train_final_bigger))[:, :, 1]
      y_val_lb_bigger = to_categorical(lb.transform(y_val_bigger))[:, :, 1]
      y_test_lb_bigger = to_categorical(lb.transform(y_test_bigger))[:, :, 1]
[47]: #
         This cell may take several minutes to run
      random.seed(123)
      bigger_data_model = models.Sequential()
      bigger_data_model.add(layers.Dense(50, activation='relu', input_shape=(2000,)))
      bigger_data_model.add(layers.Dense(25, activation='relu'))
      bigger_data_model.add(layers.Dense(7, activation='softmax'))
      bigger_data_model.compile(optimizer='SGD',
                                loss='categorical_crossentropy',
                                metrics=['acc'])
      bigger_data_model_val = bigger_data_model.fit(X_train_tokens_bigger,
                                                    y_train_lb_bigger,
```

```
epochs=150,
                     batch_size=256,
→validation_data=(X_val_tokens_bigger, y_val_lb_bigger))
Epoch 1/150
0.2189 - val_loss: 1.8419 - val_acc: 0.2767
Epoch 2/150
0.3603 - val_loss: 1.5798 - val_acc: 0.4322
Epoch 3/150
0.5080 - val_loss: 1.2865 - val_acc: 0.5673
Epoch 4/150
0.6249 - val_loss: 1.0664 - val_acc: 0.6547
Epoch 5/150
0.6805 - val_loss: 0.9251 - val_acc: 0.6913
0.7081 - val_loss: 0.8356 - val_acc: 0.7088
Epoch 7/150
0.7264 - val_loss: 0.7777 - val_acc: 0.7232
Epoch 8/150
0.7389 - val_loss: 0.7356 - val_acc: 0.7352
Epoch 9/150
0.7495 - val_loss: 0.7061 - val_acc: 0.7415
Epoch 10/150
0.7575 - val_loss: 0.6844 - val_acc: 0.7490
Epoch 11/150
0.7650 - val_loss: 0.6674 - val_acc: 0.7558
```

```
Epoch 12/150
0.7713 - val_loss: 0.6556 - val_acc: 0.7600
Epoch 13/150
0.7765 - val_loss: 0.6427 - val_acc: 0.7590
Epoch 14/150
0.7807 - val_loss: 0.6314 - val_acc: 0.7660
```

```
Epoch 15/150
0.7858 - val_loss: 0.6228 - val_acc: 0.7700
Epoch 16/150
0.7908 - val_loss: 0.6155 - val_acc: 0.7747
Epoch 17/150
0.7946 - val_loss: 0.6103 - val_acc: 0.7795
Epoch 18/150
0.7979 - val_loss: 0.6003 - val_acc: 0.7835
Epoch 19/150
0.8012 - val_loss: 0.5995 - val_acc: 0.7835
Epoch 20/150
0.8047 - val_loss: 0.5938 - val_acc: 0.7887
Epoch 21/150
0.8077 - val_loss: 0.5911 - val_acc: 0.7837
Epoch 22/150
0.8102 - val_loss: 0.5820 - val_acc: 0.7915
Epoch 23/150
0.8134 - val_loss: 0.5848 - val_acc: 0.7875
Epoch 24/150
0.8157 - val_loss: 0.5750 - val_acc: 0.7928
Epoch 25/150
0.8186 - val_loss: 0.5718 - val_acc: 0.7952
Epoch 26/150
0.8211 - val_loss: 0.5723 - val_acc: 0.7983
Epoch 27/150
0.8228 - val_loss: 0.5696 - val_acc: 0.7937
Epoch 28/150
0.8248 - val_loss: 0.5692 - val_acc: 0.7972
Epoch 29/150
0.8273 - val_loss: 0.5644 - val_acc: 0.8025
Epoch 30/150
0.8278 - val_loss: 0.5610 - val_acc: 0.8018
```

```
Epoch 31/150
0.8291 - val_loss: 0.5620 - val_acc: 0.7925
Epoch 32/150
0.8313 - val_loss: 0.5574 - val_acc: 0.8010
Epoch 33/150
0.8330 - val_loss: 0.5541 - val_acc: 0.8035
Epoch 34/150
0.8348 - val_loss: 0.5538 - val_acc: 0.8027
Epoch 35/150
0.8365 - val_loss: 0.5565 - val_acc: 0.7983
Epoch 36/150
0.8376 - val_loss: 0.5500 - val_acc: 0.8048
Epoch 37/150
0.8391 - val_loss: 0.5517 - val_acc: 0.8060
Epoch 38/150
0.8409 - val_loss: 0.5502 - val_acc: 0.8060
Epoch 39/150
0.8419 - val_loss: 0.5482 - val_acc: 0.8075
Epoch 40/150
0.8441 - val_loss: 0.5479 - val_acc: 0.8070
Epoch 41/150
0.8447 - val_loss: 0.5504 - val_acc: 0.8075
Epoch 42/150
0.8454 - val_loss: 0.5471 - val_acc: 0.8070
Epoch 43/150
0.8464 - val_loss: 0.5483 - val_acc: 0.8058
Epoch 44/150
0.8486 - val_loss: 0.5451 - val_acc: 0.8108
Epoch 45/150
0.8494 - val_loss: 0.5448 - val_acc: 0.8083
Epoch 46/150
0.8504 - val_loss: 0.5476 - val_acc: 0.8115
```

```
Epoch 47/150
0.8512 - val_loss: 0.5445 - val_acc: 0.8080
Epoch 48/150
0.8532 - val_loss: 0.5452 - val_acc: 0.8085
Epoch 49/150
0.8533 - val_loss: 0.5491 - val_acc: 0.8095
Epoch 50/150
0.8548 - val_loss: 0.5464 - val_acc: 0.8080
Epoch 51/150
0.8548 - val_loss: 0.5436 - val_acc: 0.8077
Epoch 52/150
0.8558 - val_loss: 0.5519 - val_acc: 0.8065
Epoch 53/150
0.8562 - val_loss: 0.5449 - val_acc: 0.8112
Epoch 54/150
0.8571 - val_loss: 0.5461 - val_acc: 0.8105
Epoch 55/150
0.8584 - val_loss: 0.5441 - val_acc: 0.8073
Epoch 56/150
0.8593 - val_loss: 0.5458 - val_acc: 0.8115
Epoch 57/150
0.8591 - val_loss: 0.5478 - val_acc: 0.8073
Epoch 58/150
0.8602 - val_loss: 0.5484 - val_acc: 0.8077
Epoch 59/150
0.8612 - val_loss: 0.5461 - val_acc: 0.8110
Epoch 60/150
0.8618 - val_loss: 0.5441 - val_acc: 0.8112
Epoch 61/150
0.8618 - val_loss: 0.5476 - val_acc: 0.8090
Epoch 62/150
0.8631 - val_loss: 0.5461 - val_acc: 0.8127
```

```
Epoch 63/150
0.8646 - val_loss: 0.5457 - val_acc: 0.8112
Epoch 64/150
0.8639 - val_loss: 0.5450 - val_acc: 0.8112
Epoch 65/150
0.8641 - val_loss: 0.5484 - val_acc: 0.8090
Epoch 66/150
0.8650 - val_loss: 0.5536 - val_acc: 0.8073
Epoch 67/150
0.8659 - val_loss: 0.5505 - val_acc: 0.8110
Epoch 68/150
0.8657 - val_loss: 0.5505 - val_acc: 0.8083
Epoch 69/150
0.8680 - val_loss: 0.5461 - val_acc: 0.8112
Epoch 70/150
0.8676 - val_loss: 0.5463 - val_acc: 0.8112
Epoch 71/150
0.8688 - val_loss: 0.5498 - val_acc: 0.8098
Epoch 72/150
0.8682 - val_loss: 0.5471 - val_acc: 0.8090
Epoch 73/150
0.8685 - val_loss: 0.5489 - val_acc: 0.8100
Epoch 74/150
0.8693 - val_loss: 0.5493 - val_acc: 0.8110
Epoch 75/150
0.8697 - val_loss: 0.5498 - val_acc: 0.8098
Epoch 76/150
0.8702 - val_loss: 0.5530 - val_acc: 0.8115
Epoch 77/150
0.8703 - val_loss: 0.5503 - val_acc: 0.8102
Epoch 78/150
0.8715 - val_loss: 0.5502 - val_acc: 0.8120
```

```
Epoch 79/150
0.8723 - val_loss: 0.5524 - val_acc: 0.8098
Epoch 80/150
0.8722 - val_loss: 0.5556 - val_acc: 0.8077
Epoch 81/150
0.8725 - val_loss: 0.5551 - val_acc: 0.8083
Epoch 82/150
0.8726 - val_loss: 0.5531 - val_acc: 0.8110
Epoch 83/150
0.8738 - val_loss: 0.5552 - val_acc: 0.8108
Epoch 84/150
0.8735 - val_loss: 0.5535 - val_acc: 0.8117
Epoch 85/150
0.8742 - val_loss: 0.5540 - val_acc: 0.8100
Epoch 86/150
0.8747 - val_loss: 0.5639 - val_acc: 0.8055
Epoch 87/150
0.8753 - val_loss: 0.5534 - val_acc: 0.8085
Epoch 88/150
0.8756 - val_loss: 0.5593 - val_acc: 0.8073
Epoch 89/150
0.8759 - val_loss: 0.5604 - val_acc: 0.8108
Epoch 90/150
0.8766 - val_loss: 0.5542 - val_acc: 0.8110
Epoch 91/150
0.8771 - val_loss: 0.5608 - val_acc: 0.8067
Epoch 92/150
0.8773 - val_loss: 0.5571 - val_acc: 0.8098
Epoch 93/150
0.8773 - val_loss: 0.5604 - val_acc: 0.8070
Epoch 94/150
0.8786 - val_loss: 0.5575 - val_acc: 0.8095
```

```
Epoch 95/150
0.8784 - val_loss: 0.5581 - val_acc: 0.8092
Epoch 96/150
0.8781 - val_loss: 0.5612 - val_acc: 0.8120
Epoch 97/150
0.8788 - val_loss: 0.5741 - val_acc: 0.8008
Epoch 98/150
0.8793 - val_loss: 0.5612 - val_acc: 0.8090
Epoch 99/150
0.8799 - val_loss: 0.5682 - val_acc: 0.8035
Epoch 100/150
0.8801 - val_loss: 0.5620 - val_acc: 0.8108
Epoch 101/150
0.8808 - val_loss: 0.5687 - val_acc: 0.8062
Epoch 102/150
0.8809 - val_loss: 0.5630 - val_acc: 0.8090
Epoch 103/150
0.8807 - val_loss: 0.5625 - val_acc: 0.8100
Epoch 104/150
0.8813 - val_loss: 0.5669 - val_acc: 0.8102
Epoch 105/150
0.8823 - val_loss: 0.5654 - val_acc: 0.8083
Epoch 106/150
0.8822 - val_loss: 0.5637 - val_acc: 0.8098
Epoch 107/150
0.8821 - val_loss: 0.5646 - val_acc: 0.8083
Epoch 108/150
0.8834 - val_loss: 0.5734 - val_acc: 0.8048
Epoch 109/150
0.8839 - val_loss: 0.5678 - val_acc: 0.8060
Epoch 110/150
0.8840 - val_loss: 0.5718 - val_acc: 0.8080
```

```
Epoch 111/150
0.8845 - val_loss: 0.5700 - val_acc: 0.8060
Epoch 112/150
0.8846 - val_loss: 0.5711 - val_acc: 0.8077
Epoch 113/150
0.8848 - val_loss: 0.5724 - val_acc: 0.8067
Epoch 114/150
0.8848 - val_loss: 0.5689 - val_acc: 0.8083
Epoch 115/150
0.8852 - val_loss: 0.5735 - val_acc: 0.8055
Epoch 116/150
0.8853 - val_loss: 0.5696 - val_acc: 0.8105
Epoch 117/150
0.8866 - val_loss: 0.5818 - val_acc: 0.8040
Epoch 118/150
0.8862 - val_loss: 0.5778 - val_acc: 0.8052
Epoch 119/150
0.8867 - val_loss: 0.5721 - val_acc: 0.8105
Epoch 120/150
0.8866 - val_loss: 0.5769 - val_acc: 0.8052
Epoch 121/150
0.8874 - val_loss: 0.5811 - val_acc: 0.8085
Epoch 122/150
0.8871 - val_loss: 0.5749 - val_acc: 0.8083
Epoch 123/150
0.8881 - val_loss: 0.5763 - val_acc: 0.8080
Epoch 124/150
0.8883 - val_loss: 0.5814 - val_acc: 0.8060
Epoch 125/150
0.8890 - val_loss: 0.5847 - val_acc: 0.8043
Epoch 126/150
0.8891 - val_loss: 0.5768 - val_acc: 0.8087
```

```
Epoch 127/150
0.8895 - val_loss: 0.5774 - val_acc: 0.8108
Epoch 128/150
0.8891 - val_loss: 0.5791 - val_acc: 0.8095
Epoch 129/150
0.8902 - val_loss: 0.5840 - val_acc: 0.8087
Epoch 130/150
0.8909 - val_loss: 0.5795 - val_acc: 0.8095
Epoch 131/150
0.8910 - val_loss: 0.5859 - val_acc: 0.8062
Epoch 132/150
0.8908 - val_loss: 0.5973 - val_acc: 0.8025
Epoch 133/150
0.8906 - val_loss: 0.5858 - val_acc: 0.8070
Epoch 134/150
0.8919 - val_loss: 0.5837 - val_acc: 0.8077
Epoch 135/150
0.8921 - val_loss: 0.5864 - val_acc: 0.8067
Epoch 136/150
0.8925 - val_loss: 0.5872 - val_acc: 0.8087
Epoch 137/150
0.8926 - val_loss: 0.5862 - val_acc: 0.8092
Epoch 138/150
0.8923 - val_loss: 0.5968 - val_acc: 0.8037
Epoch 139/150
0.8933 - val_loss: 0.5884 - val_acc: 0.8077
Epoch 140/150
0.8932 - val_loss: 0.5880 - val_acc: 0.8083
Epoch 141/150
0.8933 - val_loss: 0.5925 - val_acc: 0.8090
Epoch 142/150
0.8941 - val_loss: 0.5917 - val_acc: 0.8077
```

```
Epoch 143/150
  0.8941 - val_loss: 0.5878 - val_acc: 0.8105
  Epoch 144/150
  0.8946 - val_loss: 0.5966 - val_acc: 0.8010
  Epoch 145/150
  0.8959 - val_loss: 0.5984 - val_acc: 0.7997
  Epoch 146/150
  0.8960 - val_loss: 0.5967 - val_acc: 0.8033
  Epoch 147/150
  0.8950 - val_loss: 0.5987 - val_acc: 0.8052
  Epoch 148/150
  0.8959 - val_loss: 0.6024 - val_acc: 0.8020
  Epoch 149/150
  0.8968 - val_loss: 0.6021 - val_acc: 0.8005
  Epoch 150/150
  0.8965 - val_loss: 0.5982 - val_acc: 0.8085
[48]: results_train = bigger_data_model.evaluate(X_train_tokens_bigger,_u
   →y_train_lb_bigger)
   print(f'Training Loss: {results_train[0]:.3} \nTraining Accuracy:

¬{results_train[1]:.3}')
   print('----')
   results_test = bigger_data_model.evaluate(X_val_tokens_bigger, y_val_lb_bigger)
   print(f'Test Loss: {results_test[0]:.3} \nTest Accuracy: {results_test[1]:.3}')
  0.9011
  Training Loss: 0.293
  Training Accuracy: 0.901
  0.8085
  Test Loss: 0.598
  Test Accuracy: 0.808
```

With the same amount of epochs and no regularization technique, you were able to get both better test accuracy and loss. You can still consider early stopping, L1, L2 and dropout here. It's clear that having more data has a strong impact on model performance!

1.16 Additional Resources

- $\bullet \ \ https://github.com/susanli2016/Machine-Learning-with-Python/blob/master/Consumer_complaints.ipynbulker/Consumer_comp$
- $\bullet \ \ https://machinelearningmastery.com/dropout-regularization-deep-learning-models-keras/$
- $\bullet \ \ https://catalog.data.gov/dataset/consumer-complaint-database$

1.17 Summary

In this lesson, you built deep learning models using a validation set and used several techniques such as L2 and L1 regularization, dropout regularization, and early stopping to improve the accuracy of your models.