Week 2: Diving deeper into the BBC News archive

Welcome! In this assignment you will be revisiting the BBC News Classification Dataset, which contains 2225 examples of news articles with their respective labels.

This time you will not only work with the tokenization process but you will also create a classifier using specialized layers for text data such as Embedding and GlobalAveragePooling1D.

Let's get started!

```
# IMPORTANT: This will check your notebook's metadata for grading.
# Please do not continue the lab unless the output of this cell tells you to proceed.
!python add_metadata.py --filename C3W2_Assignment.ipynb
```

```
Grader metadata detected! You can proceed with the lab!
```

NOTE: *To prevent errors from the autograder, you are not allowed to edit or delete non-graded cells in this notebook . Please only put your solutions in between the* `### START CODE HERE` *and* `### END CODE HERE` *code comments, and also refrain from adding any new cells.* ***Once you have passed this assignment*** *and want to experiment with any of the non-graded code, you may follow the instructions at the bottom of this notebook.*

```
# grader-required-cell

import io
import csv
import tensorflow as tf
import numpy as np
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
import matplotlib.pyplot as plt
```

You probably remember structure of the csv that contains the data from last week, but in case you need a reminder run the next cell:

```
# grader-required-cell

with open("./bbc-text.csv", 'r') as csvfile:
    print(f"First line (header) looks like this:\n\n{csvfile.readline()}")
    print(f"Each data point looks like this:\n\n{csvfile.readline()}")
```

```
First line (header) looks like this:
```

```
category,text

Each data point looks like this:

tech,tv future in the hands of viewers with home theatre systems
plasma high-definition tvs  and digital video recorders moving into
the living room  the way people watch tv will be radically different
in five years  time.  that is according to an expert panel which
gathered at the annual consumer electronics show in las vegas to
discuss how these new technologies will impact one of our favourite
pastimes. with the us leading the trend  programmes and other content
will be delivered to viewers via home networks  through cable
satellite  telecoms companies  and broadband service providers to
front rooms and portable devices.  one of the most talked-about
technologies of ces has been digital and personal video recorders (dvr
and pvr). these set-top boxes  like the us s tivo and the uk s sky+
system  allow people to record  store  play  pause and forward wind tv
programmes when they want.  essentially  the technology allows for
much more personalised tv. they are also being built-in to high-
definition tv sets  which are big business in japan and the us  but
slower to take off in europe because of the lack of high-definition
programming. not only can people forward wind through adverts  they
can also forget about abiding by network and channel schedules
putting together their own a-la-carte entertainment. but some us
networks and cable and satellite companies are worried about what it
means for them in terms of advertising revenues as well as  brand
identity  and viewer loyalty to channels. although the us leads in
this technology at the moment  it is also a concern that is being
raised in europe  particularly with the growing uptake of services
like sky+.  what happens here today  we will see in nine months to a
years  time in the uk   adam hume  the bbc broadcast s futurologist
told the bbc news website. for the likes of the bbc  there are no
issues of lost advertising revenue yet. it is a more pressing issue at
the moment for commercial uk broadcasters  but brand loyalty is
important for everyone.  we will be talking more about content brands
rather than network brands   said tim hanlon  from brand
communications firm starcom mediavest.  the reality is that with
broadband connections  anybody can be the producer of content.  he
added:  the challenge now is that it is hard to promote a programme
with so much choice.   what this means  said stacey jolna  senior vice
president of tv guide tv group  is that the way people find the
content they want to watch has to be simplified for tv viewers. it
means that networks  in us terms  or channels could take a leaf out of
google s book and be the search engine of the future  instead of the
scheduler to help people find what they want to watch. this kind of
channel model might work for the younger ipod generation which is used
to taking control of their gadgets and what they play on them. but it
might not suit everyone  the panel recognised. older generations are
more comfortable with familiar schedules and channel brands because
```

```
they know what they are getting. they perhaps do not want so much of
the choice put into their hands  mr hanlon suggested.  on the other
end  you have the kids just out of diapers who are pushing buttons
already - everything is possible and available to them   said mr
hanlon.  ultimately  the consumer will tell the market they want.   of
the 50 000 new gadgets and technologies being showcased at ces  many
of them are about enhancing the tv-watching experience. high-
definition tv sets are everywhere and many new models of lcd (liquid
crystal display) tvs have been launched with dvr capability built into
them  instead of being external boxes. one such example launched at
the show is humax s 26-inch lcd tv with an 80-hour tivo dvr and dvd
recorder. one of the us s biggest satellite tv companies  directtv
has even launched its own branded dvr at the show with 100-hours of
recording capability  instant replay  and a search function. the set
can pause and rewind tv for up to 90 hours. and microsoft chief bill
gates announced in his pre-show keynote speech a partnership with tivo
called tivotogo  which means people can play recorded programmes on
windows pcs and mobile devices. all these reflect the increasing trend
of freeing up multimedia so that people can watch what they want  when
they want.
```

As you can see, each data point is composed of the category of the news article followed by a comma and then the actual text of the article.

Defining useful global variables

Next, you will define some global variables that will be used in the unit tests after your solutions. **Please do not use these in the function body of the graded functions.**

- `NUM_WORDS`: The maximum number of words to keep, based on word frequency. Defaults to 1000.

- `EMBEDDING_DIM`: Dimensionality of the dense embedding, will be used in the embedding layer of the model. Defaults to 16.

- `MAXLEN`: Maximum length of all sequences. Defaults to 120.

- `PADDING`: Padding strategy (pad either before or after each sequence.). Defaults to 'post'.

- `OOV_TOKEN`: Token to replace out-of-vocabulary words during text_to_sequence calls. Defaults to "<OOV>".

- `TRAINING_SPLIT`: Proportion of data used for training. Defaults to 0.8

For now leave them unchanged but after submitting your assignment for grading you are encouraged to come back here and play with these parameters to see the impact they have in the classification process

```python
# grader-required-cell

NUM_WORDS = 1000
EMBEDDING_DIM = 16
MAXLEN = 120
PADDING = 'post'
OOV_TOKEN = "<OOV>"
TRAINING_SPLIT = .8
```

Loading and pre-processing the data

Now you should code the functions to remove stopwords from text and to load the data from a csv file.

Since you already coded these functions for the previous week, these are provided for you.

```python
# grader-required-cell

def remove_stopwords(sentence):
    """
    Removes a list of stopwords

    Args:
        sentence (string): sentence to remove the stopwords from

    Returns:
        sentence (string): lowercase sentence without the stopwords
    """
    # List of stopwords
    stopwords = ["a", "about", "above", "after", "again", "against",
"all", "am", "an", "and", "any", "are", "as", "at", "be", "because",
"been", "before", "being", "below", "between", "both", "but", "by",
"could", "did", "do", "does", "doing", "down", "during", "each",
"few", "for", "from", "further", "had", "has", "have", "having", "he",
"he'd", "he'll", "he's", "her", "here", "here's", "hers", "herself",
"him", "himself", "his", "how", "how's", "i", "i'd", "i'll", "i'm",
"i've", "if", "in", "into", "is", "it", "it's", "its", "itself",
"let's", "me", "more", "most", "my", "myself", "nor", "of", "on",
"once", "only", "or", "other", "ought", "our", "ours", "ourselves",
"out", "over", "own", "same", "she", "she'd", "she'll", "she's",
"should", "so", "some", "such", "than", "that", "that's", "the",
"their", "theirs", "them", "themselves", "then", "there", "there's",
"these", "they", "they'd", "they'll", "they're", "they've", "this",
"those", "through", "to", "too", "under", "until", "up", "very",
"was", "we", "we'd", "we'll", "we're", "we've", "were", "what",
"what's", "when", "when's", "where", "where's", "which", "while",
"who", "who's", "whom", "why", "why's", "with", "would", "you",
"you'd", "you'll", "you're", "you've", "your", "yours", "yourself",
"yourselves" ]
```

```
    # Sentence converted to lowercase-only
    sentence = sentence.lower()

    words = sentence.split()
    no_words = [w for w in words if w not in stopwords]
    sentence = " ".join(no_words)

    return sentence


def parse_data_from_file(filename):
    """
    Extracts sentences and labels from a CSV file

    Args:
        filename (string): path to the CSV file

    Returns:
        sentences, labels (list of string, list of string): tuple
containing lists of sentences and labels
    """
    sentences = []
    labels = []
    with open(filename, 'r') as csvfile:
        reader = csv.reader(csvfile, delimiter=',')
        next(reader)
        for row in reader:
            labels.append(row[0])
            sentence = row[1]
            sentence = remove_stopwords(sentence)
            sentences.append(sentence)

    return sentences, labels

# grader-required-cell

# Test the functions
sentences, labels = parse_data_from_file("./bbc-text.csv")

print(f"There are {len(sentences)} sentences in the dataset.\n")
print(f"First sentence has {len(sentences[0].split())} words (after
removing stopwords).\n")
print(f"There are {len(labels)} labels in the dataset.\n")
print(f"The first 5 labels are {labels[:5]}")
```

```
There are 2225 sentences in the dataset.

First sentence has 436 words (after removing stopwords).

There are 2225 labels in the dataset.
```

```
The first 5 labels are ['tech', 'business', 'sport', 'sport',
'entertainment']
```

Expected Output:

```
There are 2225 sentences in the dataset.

First sentence has 436 words (after removing stopwords).

There are 2225 labels in the dataset.

The first 5 labels are ['tech', 'business', 'sport', 'sport',
'entertainment']
```

Training - Validation Split

Now you will code the `train_val_split()` function. Given the training split size, this function will split the full lists of sentences and labels into training and validation sentences and labels.

IMPORTANT NOTE: For all graded functions in this assignment, please do not use the global variables (e.g. `TRAINING_SPLIT`) in your solution. Instead, you should use the function parameters defined in the function header (e.g. `training_split`).

```
# grader-required-cell

# GRADED FUNCTIONS: train_val_split
def train_val_split(sentences, labels, training_split):
    """
    Splits the dataset into training and validation sets

    Args:
        sentences (list of string): lower-cased sentences without
stopwords
        labels (list of string): list of labels
        training split (float): proportion of the dataset to convert
to include in the train set

    Returns:
        train_sentences, validation_sentences, train_labels,
validation_labels - lists containing the data splits
    """

    ### START CODE HERE

    # Compute the number of sentences that will be used for training
(should be an integer)
    train_size = int(len(sentences)*training_split)
```

```
    # Split the sentences and labels into train/validation splits
    train_sentences = sentences[:train_size]
    train_labels = labels[:train_size]

    validation_sentences = sentences[train_size:]
    validation_labels = labels[train_size:]

    ### END CODE HERE

    return train_sentences, validation_sentences, train_labels,
validation_labels
```

```
# grader-required-cell

# Test your function
train_sentences, val_sentences, train_labels, val_labels =
train_val_split(sentences, labels, TRAINING_SPLIT)

print(f"There are {len(train_sentences)} sentences for training.\n")
print(f"There are {len(train_labels)} labels for training.\n")
print(f"There are {len(val_sentences)} sentences for validation.\n")
print(f"There are {len(val_labels)} labels for validation.")
```

```
There are 1780 sentences for training.

There are 1780 labels for training.

There are 445 sentences for validation.

There are 445 labels for validation.
```

Expected Output:

```
There are 1780 sentences for training.

There are 1780 labels for training.

There are 445 sentences for validation.

There are 445 labels for validation.
```

Tokenization - Sequences and padding

Now that you have sets for training and validation it is time for you to begin the tokenization process.

Begin by completing the `fit_tokenizer` function below. This function should return a Tokenizer that has been fitted to the training sentences.

```python
# grader-required-cell

# GRADED FUNCTION: fit_tokenizer
def fit_tokenizer(train_sentences, num_words, oov_token):
    """
    Instantiates the Tokenizer class on the training sentences

    Args:
        train_sentences (list of string): lower-cased sentences
without stopwords to be used for training
        num_words (int) - number of words to keep when tokenizing
        oov_token (string) - symbol for the out-of-vocabulary token

    Returns:
        tokenizer (object): an instance of the Tokenizer class
containing the word-index dictionary
    """

    ### START CODE HERE

    # Instantiate the Tokenizer class, passing in the correct values
for num_words and oov_token
    tokenizer = Tokenizer(num_words=num_words, oov_token=oov_token)

    # Fit the tokenizer to the training sentences
    tokenizer.fit_on_texts(train_sentences)

    ### END CODE HERE

    return tokenizer
```

```python
# grader-required-cell

# Test your function
tokenizer = fit_tokenizer(train_sentences, NUM_WORDS, OOV_TOKEN)
word_index = tokenizer.word_index

print(f"Vocabulary contains {len(word_index)} words\n")
print("<OOV> token included in vocabulary" if "<OOV>" in word_index
else "<OOV> token NOT included in vocabulary")
```

```
Vocabulary contains 27285 words

<OOV> token included in vocabulary
```

Expected Output:

```
Vocabulary contains 27285 words

<OOV> token included in vocabulary
```

Now that the tokenizer has been fitted to the training data, you need a function that will convert each text data point into its padded sequence representation, for this complete the `seq_and_pad` function below:

```
# grader-required-cell

# GRADED FUNCTION: seq_and_pad
def seq_and_pad(sentences, tokenizer, padding, maxlen):
    """
    Generates an array of token sequences and pads them to the same
length

    Args:
        sentences (list of string): list of sentences to tokenize and
pad
        tokenizer (object): Tokenizer instance containing the word-
index dictionary
        padding (string): type of padding to use
        maxlen (int): maximum length of the token sequence

    Returns:
        padded_sequences (array of int): tokenized sentences padded to
the same length
    """

    ### START CODE HERE

    # Convert sentences to sequences
    sequences = tokenizer.texts_to_sequences(sentences)

    # Pad the sequences using the correct padding and maxlen
    padded_sequences = pad_sequences(sequences, maxlen=maxlen,
padding=padding)

    ### END CODE HERE

    return padded_sequences

# grader-required-cell

# Test your function
train_padded_seq = seq_and_pad(train_sentences, tokenizer, PADDING,
MAXLEN)
val_padded_seq = seq_and_pad(val_sentences, tokenizer, PADDING,
MAXLEN)

print(f"Padded training sequences have shape:
{train_padded_seq.shape}\n")
print(f"Padded validation sequences have shape:
{val_padded_seq.shape}")
```

```
Padded training sequences have shape: (1780, 120)

Padded validation sequences have shape: (445, 120)
```

Expected Output:

```
Padded training sequences have shape: (1780, 120)

Padded validation sequences have shape: (445, 120)
```

Finally you need to tokenize the labels. For this complete the `tokenize_labels` function below.

A couple of things to note:

- You should fit the tokenizer to all the labels to avoid the case of a particular label not being present in the validation set. Since you are dealing with labels there should never be an OOV label.
- In the previous function you used the `pad_sequences` function which returns numpy arrays. Here you will not be using it since you don't need to pad the labels so you need to make the conversion to numpy arrays yourself.
- The argument `split_labels` refers to the labels of a particular split (train or validation). This is because the function should work independently of the split being used.
- Using Keras' Tokenizer yields values that start at 1 rather than at 0. This will present a problem when training since Keras usually expects the labels to start at 0. To work around this issue you could use an extra neuron in the last layer of your model. However this approach is rather hacky and not very clear. Instead you will substract 1 from every value of the labels that the function returns. Remember that when using numpy arrays you can simply do something like `np.array - 1` to accomplish this since numpy allows for vectorized operations.

```
# grader-required-cell

# GRADED FUNCTION: tokenize_labels
def tokenize_labels(all_labels, split_labels):
    """
    Tokenizes the labels

    Args:
        all_labels (list of string): labels to generate the word-index
from
        split_labels (list of string): labels to tokenize

    Returns:
```

```
        label_seq_np (array of int): tokenized labels
    """

    ### START CODE HERE

    # Instantiate the Tokenizer (no additional arguments needed)
    label_tokenizer = Tokenizer()

    # Fit the tokenizer on all the labels
    label_tokenizer.fit_on_texts(all_labels)

    # Convert labels to sequences
    label_seq = label_tokenizer.texts_to_sequences(split_labels)

    # Convert sequences to a numpy array. Don't forget to substact 1
from every entry in the array!
    label_seq_np = np.array(label_seq)-1

    ### END CODE HERE

    return label_seq_np

# grader-required-cell

# Test your function
train_label_seq = tokenize_labels(labels, train_labels)
val_label_seq = tokenize_labels(labels, val_labels)

print(f"First 5 labels of the training set should look like this:\
n{train_label_seq[:5]}\n")
print(f"First 5 labels of the validation set should look like this:\
n{val_label_seq[:5]}\n")
print(f"Tokenized labels of the training set have shape:
{train_label_seq.shape}\n")
print(f"Tokenized labels of the validation set have shape:
{val_label_seq.shape}\n")

First 5 labels of the training set should look like this:
[[3]
 [1]
 [0]
 [0]
 [4]]

First 5 labels of the validation set should look like this:
[[4]
 [3]
 [2]
 [0]
 [0]]
```

```
Tokenized labels of the training set have shape: (1780, 1)

Tokenized labels of the validation set have shape: (445, 1)
```

Expected Output:

```
First 5 labels of the training set should look like this:
[[3]
 [1]
 [0]
 [0]
 [4]]

First 5 labels of the validation set should look like this:
[[4]
 [3]
 [2]
 [0]
 [0]]

Tokenized labels of the training set have shape: (1780, 1)

Tokenized labels of the validation set have shape: (445, 1)
```

Selecting the model for text classification

Now that the data is ready to be fed a Neural Network it is time for you to define the model that will classify each text as being part of a certain category.

For this complete the `create_model` below.

A couple of things to keep in mind:

- Notice that this function has three parameters, all of which are meant to be passed to an Embedding layer, which is what you will probably use as a first layer for your model.
- The last layer should be a Dense layer with 5 units (since there are 5 categories) with a softmax activation.
- You should also compile your model using an appropiate loss function and optimizer. Please choose these without needing to edit the following code cell that contains `model.fit()`
- You can use any architecture you want but keep in mind that this problem doesn't need many layers to be solved successfully. You don't need any layers beside Embedding, GlobalAveragePooling1D and Dense layers but feel free to try out different architectures.

- **To pass this graded function your model should reach at least a 95% training accuracy and a 90% validation accuracy in under 30 epochs.**

```
# grader-required-cell

# GRADED FUNCTION: create_model
def create_model(num_words, embedding_dim, maxlen):
    """
    Creates a text classifier model

    Args:
        num_words (int): size of the vocabulary for the Embedding 
layer input
        embedding_dim (int): dimensionality of the Embedding layer 
output
        maxlen (int): length of the input sequences

    Returns:
        model (tf.keras Model): the text classifier model
    """

    tf.random.set_seed(123)

    ### START CODE HERE

    model = tf.keras.Sequential([
        tf.keras.layers.Embedding(num_words, embedding_dim, 
input_length=maxlen),
        tf.keras.layers.GlobalAveragePooling1D(),
        tf.keras.layers.Dense(35, activation='relu'),
        tf.keras.layers.Dense(5, activation='softmax')
    ])

    model.compile(loss='sparse_categorical_crossentropy',
                  optimizer='adam',
                  metrics=['accuracy'])

    ### END CODE HERE

    return model

# NOTE: Please do not edit this cell

model = create_model(NUM_WORDS, EMBEDDING_DIM, MAXLEN)

history = model.fit(train_padded_seq, train_label_seq, epochs=30, 
validation_data=(val_padded_seq, val_label_seq))

Epoch 1/30
56/56 [==============================] - 1s 4ms/step - loss: 1.6008 -
```

```
accuracy: 0.2303 - val_loss: 1.5865 - val_accuracy: 0.3955
Epoch 2/30
56/56 [==============================] - 0s 2ms/step - loss: 1.5600 -
accuracy: 0.4281 - val_loss: 1.5185 - val_accuracy: 0.4247
Epoch 3/30
56/56 [==============================] - 0s 2ms/step - loss: 1.4418 -
accuracy: 0.4539 - val_loss: 1.3555 - val_accuracy: 0.4607
Epoch 4/30
56/56 [==============================] - 0s 2ms/step - loss: 1.2191 -
accuracy: 0.5096 - val_loss: 1.1142 - val_accuracy: 0.5843
Epoch 5/30
56/56 [==============================] - 0s 2ms/step - loss: 0.9565 -
accuracy: 0.7331 - val_loss: 0.8773 - val_accuracy: 0.7888
Epoch 6/30
56/56 [==============================] - 0s 2ms/step - loss: 0.7167 -
accuracy: 0.8843 - val_loss: 0.6726 - val_accuracy: 0.8921
Epoch 7/30
56/56 [==============================] - 0s 2ms/step - loss: 0.5228 -
accuracy: 0.9371 - val_loss: 0.5185 - val_accuracy: 0.9124
Epoch 8/30
56/56 [==============================] - 0s 2ms/step - loss: 0.3874 -
accuracy: 0.9478 - val_loss: 0.4149 - val_accuracy: 0.9169
Epoch 9/30
56/56 [==============================] - 0s 2ms/step - loss: 0.2989 -
accuracy: 0.9607 - val_loss: 0.3519 - val_accuracy: 0.9191
Epoch 10/30
56/56 [==============================] - 0s 2ms/step - loss: 0.2369 -
accuracy: 0.9657 - val_loss: 0.3038 - val_accuracy: 0.9191
Epoch 11/30
56/56 [==============================] - 0s 2ms/step - loss: 0.1947 -
accuracy: 0.9702 - val_loss: 0.2739 - val_accuracy: 0.9281
Epoch 12/30
56/56 [==============================] - 0s 2ms/step - loss: 0.1632 -
accuracy: 0.9736 - val_loss: 0.2510 - val_accuracy: 0.9258
Epoch 13/30
56/56 [==============================] - 0s 2ms/step - loss: 0.1392 -
accuracy: 0.9781 - val_loss: 0.2358 - val_accuracy: 0.9326
Epoch 14/30
56/56 [==============================] - 0s 2ms/step - loss: 0.1191 -
accuracy: 0.9809 - val_loss: 0.2232 - val_accuracy: 0.9326
Epoch 15/30
56/56 [==============================] - 0s 2ms/step - loss: 0.1031 -
accuracy: 0.9831 - val_loss: 0.2095 - val_accuracy: 0.9326
Epoch 16/30
56/56 [==============================] - 0s 2ms/step - loss: 0.0895 -
accuracy: 0.9860 - val_loss: 0.2006 - val_accuracy: 0.9326
Epoch 17/30
56/56 [==============================] - 0s 2ms/step - loss: 0.0781 -
accuracy: 0.9899 - val_loss: 0.1945 - val_accuracy: 0.9348
```

```
Epoch 18/30
56/56 [==============================] - 0s 2ms/step - loss: 0.0686 - accuracy: 0.9910 - val_loss: 0.1911 - val_accuracy: 0.9348
Epoch 19/30
56/56 [==============================] - 0s 2ms/step - loss: 0.0606 - accuracy: 0.9949 - val_loss: 0.1854 - val_accuracy: 0.9348
Epoch 20/30
56/56 [==============================] - 0s 2ms/step - loss: 0.0528 - accuracy: 0.9978 - val_loss: 0.1809 - val_accuracy: 0.9416
Epoch 21/30
56/56 [==============================] - 0s 2ms/step - loss: 0.0472 - accuracy: 0.9983 - val_loss: 0.1813 - val_accuracy: 0.9371
Epoch 22/30
56/56 [==============================] - 0s 2ms/step - loss: 0.0418 - accuracy: 0.9983 - val_loss: 0.1751 - val_accuracy: 0.9416
Epoch 23/30
56/56 [==============================] - 0s 2ms/step - loss: 0.0371 - accuracy: 0.9983 - val_loss: 0.1751 - val_accuracy: 0.9393
Epoch 24/30
56/56 [==============================] - 0s 2ms/step - loss: 0.0330 - accuracy: 0.9989 - val_loss: 0.1714 - val_accuracy: 0.9416
Epoch 25/30
56/56 [==============================] - 0s 2ms/step - loss: 0.0295 - accuracy: 0.9989 - val_loss: 0.1711 - val_accuracy: 0.9416
Epoch 26/30
56/56 [==============================] - 0s 3ms/step - loss: 0.0264 - accuracy: 0.9989 - val_loss: 0.1702 - val_accuracy: 0.9416
Epoch 27/30
56/56 [==============================] - 0s 2ms/step - loss: 0.0237 - accuracy: 0.9994 - val_loss: 0.1714 - val_accuracy: 0.9393
Epoch 28/30
56/56 [==============================] - 0s 2ms/step - loss: 0.0214 - accuracy: 0.9994 - val_loss: 0.1676 - val_accuracy: 0.9416
Epoch 29/30
56/56 [==============================] - 0s 3ms/step - loss: 0.0192 - accuracy: 1.0000 - val_loss: 0.1686 - val_accuracy: 0.9416
Epoch 30/30
56/56 [==============================] - 0s 2ms/step - loss: 0.0174 - accuracy: 1.0000 - val_loss: 0.1668 - val_accuracy: 0.9438
```

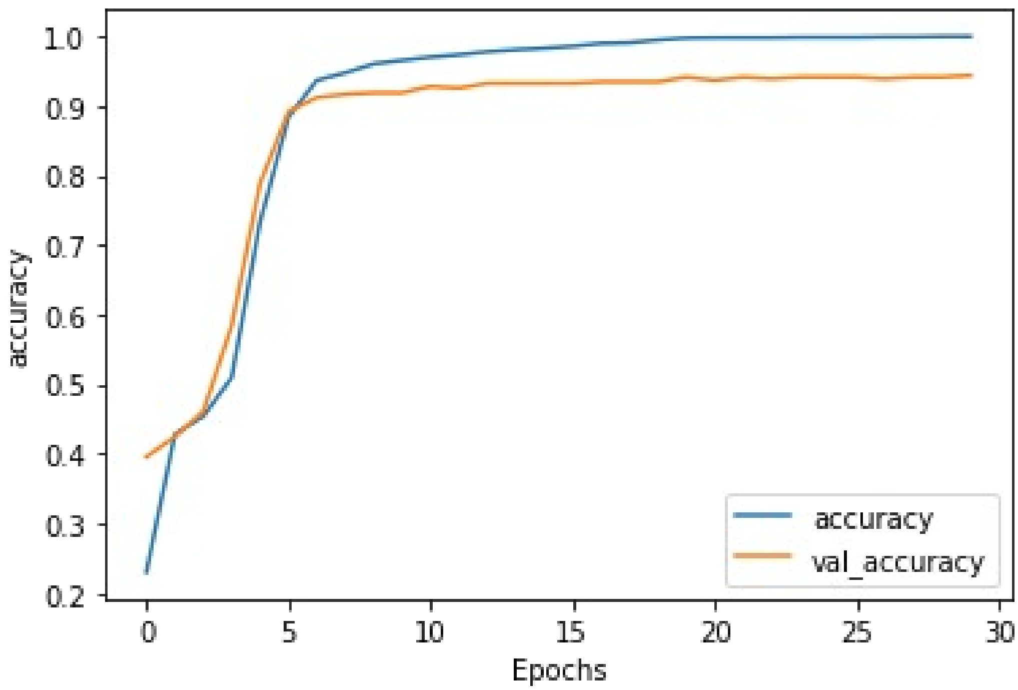
Once training has finished you can run the following cell to check the training and validation accuracy achieved at the end of each epoch.

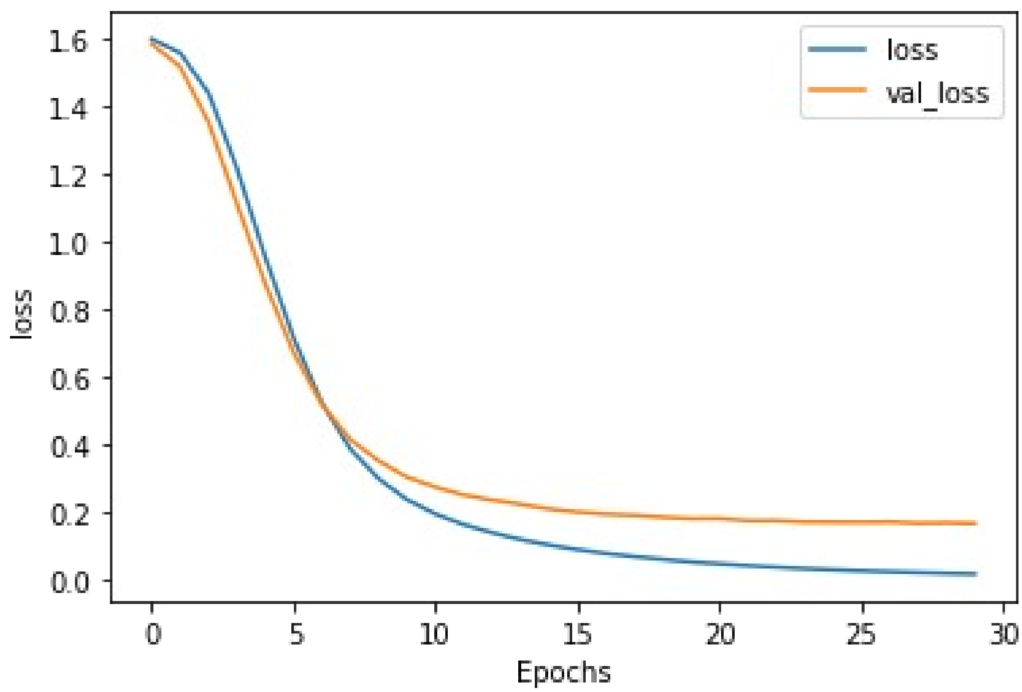
Remember that to pass this assignment your model should achieve a training accuracy of at least 95% and a validation accuracy of at least 90%. If your model didn't achieve these thresholds, try training again with a different model architecture.

```
def plot_graphs(history, metric):
    plt.plot(history.history[metric])
```

```
    plt.plot(history.history[f'val_{metric}'])
    plt.xlabel("Epochs")
    plt.ylabel(metric)
    plt.legend([metric, f'val_{metric}'])
    plt.show()

plot_graphs(history, "accuracy")
plot_graphs(history, "loss")
```





If your model passes the previously mentioned thresholds be sure to save your notebook and submit for grading before jumping onto the next section.

Optional Exercise - Visualizing 3D Vectors

As you saw on the lecture you can visualize the vectors associated with each word in the training set in a 3D space.

For this run the following cells and visit Tensorflow's Embedding Projector.

```
# Reverse word index
reverse_word_index = dict([(value, key) for (key, value) in
word_index.items()])

# Save the embedding layer
e = model.layers[0]

# Save the weights of the embedding layer
weights = e.get_weights()[0]
print(f"Weights of embedding layer have shape: {weights.shape}")

Weights of embedding layer have shape: (1000, 16)
```

Expected Output:

```
Weights of embedding layer have shape: (1000, 16)
```

```
The above is true if global variables are not modified.
Notice that this shape will always be (NUM_WORDS, EMBEDDING_DIM).
```

Now run the following cell to generate the `vecs.tsv` and `meta.tsv` files that you will upload to the embedding projector.

```
# Generate files for embedding visualization
out_v = io.open('vecs.tsv', 'w', encoding='utf-8')
out_m = io.open('meta.tsv', 'w', encoding='utf-8')
for word_num in range(1, NUM_WORDS):
    word = reverse_word_index[word_num]
    embeddings = weights[word_num]
    out_m.write(word + "\n")
    out_v.write('\t'.join([str(x) for x in embeddings]) + "\n")
out_v.close()
out_m.close()
```

Before downloading these files be sure to having already submitted your assignment.

By running the previous cell, these files are placed within your filesystem. To download them, click on the `Jupyter` logo on the upper-left side of the screen. This will take you to the Jupyter filesystem and there you can download the files by selecting them and clicking on the `Download` button.

Congratulations on finishing this week's assignment!

You have successfully implemented a neural network capable of classifying text and also learned about embeddings and tokenization along the way!

Keep it up!