ayeliped-asssignment4

November 21, 2024

[51]:
```python
import os
from operator import itemgetter
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings('ignore')
get_ipython().magic(u'matplotlib inline')
plt.style.use('ggplot')

import tensorflow as tf

from keras import models, regularizers, layers, optimizers, losses, metrics
from keras.models import Sequential
from keras.layers import Dense
from keras.utils import to_categorical
```

Both positive and negative sentiment are assigned to movie reviews in the IMDB dataset.

As part of the preprocessing of the dataset, each review is transformed into a set of word embeddings, where each word is represented by a fixed-size vector.

[52]:
```python
from keras.layers import Embedding

# The Embedding layer requires a minimum of two inputs:
# The maximum word index plus one, or 1000, is the number of potential tokens.
# and the embeddings' dimensions, in this case 64.
layEmbd = Embedding(1000, 64)

from keras.datasets import imdb
from keras import preprocessing
from keras.utils import pad_sequences
```

custom-trained embedding layer with training sample size = 100

[53]:
```python
# The number of words that should be considered as features
Fe_ature = 10000
# Remove the text after this number of words (from the top Fe_ature most common␣
↪words)
```

```
_leng = 150


(TrainingX, TrainingY), (XTesting, YTesting) = imdb.
 ↪load_data(num_words=Fe_ature)

TrainingX = TrainingX[:100]
TrainingY = TrainingY[:100]


TrainingX = pad_sequences(TrainingX, maxlen=_leng)
XTesting = pad_sequences(XTesting, maxlen=_leng)

from keras.models import Sequential
from keras.layers import Flatten, Dense

mdl = Sequential()

mdl.add(Embedding(10000, 8, input_length=_leng))

mdl.add(Flatten())

# We add the classifier on top
mdl.add(Dense(1, activation='sigmoid'))
mdl.compile(optimizer='rmsprop', loss='binary_crossentropy', metrics=['acc'])
mdl.summary()

hist_1 = mdl.fit(TrainingX, TrainingY,
                   epochs=10,
                   batch_size=32,
                   validation_split=0.2)
```

```
Model: "sequential_15"


 Layer (type)                        Output Shape                                ␣
 ↪Param #

 embedding_18 (Embedding)            ?                                        0␣
 ↪(unbuilt)

 flatten_13 (Flatten)                ?                                        0␣
 ↪(unbuilt)

 dense_21 (Dense)                    ?                                        0␣
 ↪(unbuilt)
```

Total params: 0 (0.00 B)

Trainable params: 0 (0.00 B)

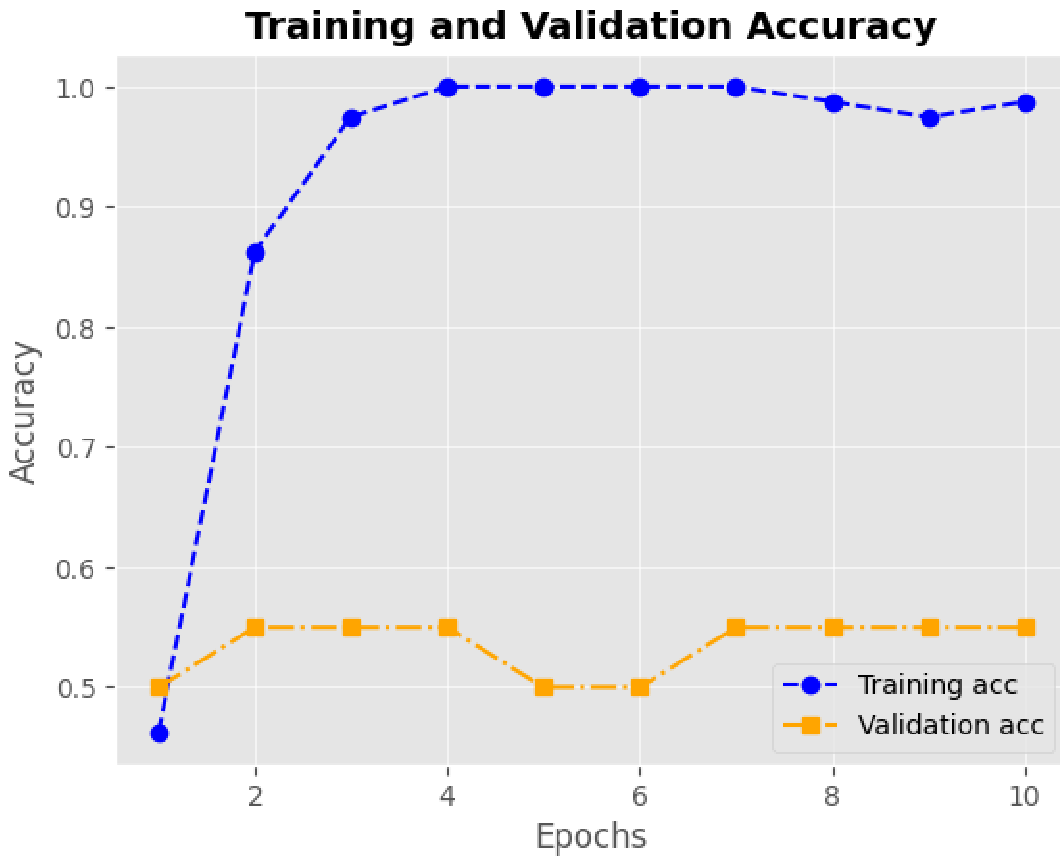
Non-trainable params: 0 (0.00 B)

```
Epoch 1/10
3/3              3s 212ms/step - acc:
0.4383 - loss: 0.6967 - val_acc: 0.5000 - val_loss: 0.6946
Epoch 2/10
3/3              0s 52ms/step - acc:
0.8961 - loss: 0.6681 - val_acc: 0.5500 - val_loss: 0.6953
Epoch 3/10
3/3              0s 52ms/step - acc:
0.9719 - loss: 0.6507 - val_acc: 0.5500 - val_loss: 0.6962
Epoch 4/10
3/3              0s 53ms/step - acc:
1.0000 - loss: 0.6324 - val_acc: 0.5500 - val_loss: 0.6971
Epoch 5/10
3/3              0s 67ms/step - acc:
1.0000 - loss: 0.6176 - val_acc: 0.5000 - val_loss: 0.6982
Epoch 6/10
3/3              0s 61ms/step - acc:
1.0000 - loss: 0.6000 - val_acc: 0.5000 - val_loss: 0.6994
Epoch 7/10
3/3              0s 62ms/step - acc:
1.0000 - loss: 0.5846 - val_acc: 0.5500 - val_loss: 0.7012
Epoch 8/10
3/3              0s 44ms/step - acc:
0.9898 - loss: 0.5680 - val_acc: 0.5500 - val_loss: 0.7033
Epoch 9/10
3/3              0s 42ms/step - acc:
0.9719 - loss: 0.5460 - val_acc: 0.5500 - val_loss: 0.7044
Epoch 10/10
3/3              0s 36ms/step - acc:
0.9820 - loss: 0.5278 - val_acc: 0.5500 - val_loss: 0.7058
```

[54]:

```python
import matplotlib.pyplot as pl

# Train accuracy
a_c_c = hist_1.history["acc"]
# Validation accuracy
val_a_c_c = hist_1.history["val_acc"]
```

```
# Train loss
lssTr_ain = hist_1.history["loss"]
# Validation loss
lssVal = hist_1.history["val_loss"]

_epochs = range(1, len(a_c_c) + 1)

pl.plot(_epochs, a_c_c, color="blue", linestyle="--", marker="o", label="Training acc")
pl.plot(_epochs, val_a_c_c, color="orange", linestyle="-.", marker="s", label="Validation acc")
pl.title("Training and Validation Accuracy", fontsize=14, fontweight='bold')
pl.xlabel("Epochs")
pl.ylabel("Accuracy")
pl.legend()
pl.grid(alpha=0.6)
pl.figure()


pl.plot(_epochs, lssTr_ain, color="purple", linestyle=":", marker="d", label="Training loss")
pl.plot(_epochs, lssVal, color="teal", linestyle="-", marker="^", label="Validation loss")
pl.title("Training and Validation Loss", fontsize=14, fontweight='bold')
pl.xlabel("Epochs")
pl.ylabel("Loss")
pl.legend()
pl.grid(alpha=0.6)

pl.show()
```


Training and Validation Accuracy
1.0
0.9
0.8
0.7
0.6
0.5
Accuracy
2
4
6
8
10
Epochs
Training acc
Validation acc

[56]:
```
tst_lss, tst_a_c_c = mdl.evaluate(XTesting, YTesting)
print('Test loss:', tst_lss)
print('Test accuracy:', tst_a_c_c)
```

```
782/782              1s 1ms/step -
acc: 0.4938 - loss: 0.6947
Test loss: 0.6948661804199219
Test accuracy: 0.4943599998950958
```

[55]:
```
Fe_ature = 10000
_leng = 150

(TrainingX, TrainingY), (XTesting, YTesting) = imdb.
  ↪load_data(num_words=Fe_ature)

TrainingX = pad_sequences(TrainingX, maxlen=_leng)
XTesting = pad_sequences(XTesting, maxlen=_leng)

comb_texts = np.concatenate((TrainingX, XTesting), axis=0)
comb_labels = np.concatenate((TrainingY, YTesting), axis=0)
```

```
TrainingX = TrainingX[:5000]
TrainingY = TrainingY[:5000]
```

[57]:
```
mdl2 = Sequential()
mdl2.add(Embedding(10000, 8, input_length=_leng))
mdl2.add(Flatten())
mdl2.add(Dense(1, activation='sigmoid'))
mdl2.compile(optimizer='rmsprop', loss='binary_crossentropy', metrics=['acc'])
mdl2.summary()

hist_2 = mdl2.fit(TrainingX, TrainingY,
                  epochs=10,
                  batch_size=32,
                  validation_split=0.2)
```

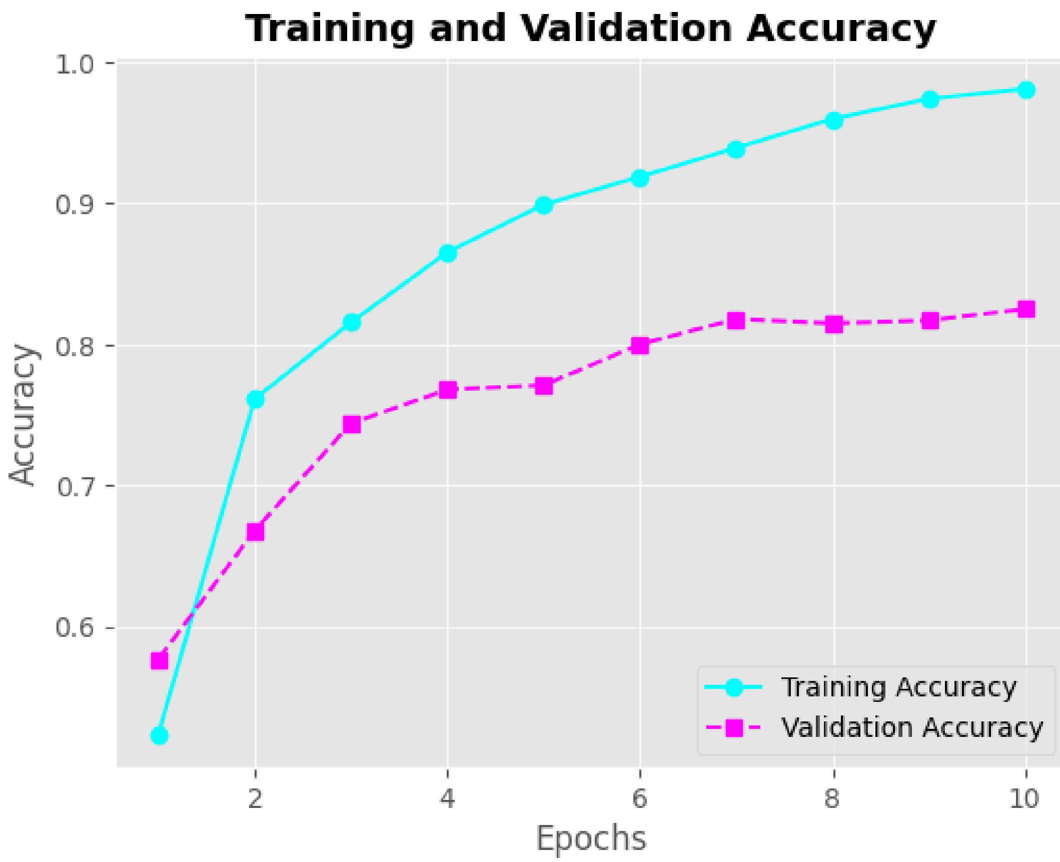
```
Model: "sequential_16"


 Layer (type)                      Output Shape                              ␣
↪Param #

 embedding_19 (Embedding)          ?                                      0␣
↪(unbuilt)

 flatten_14 (Flatten)              ?                                      0␣
↪(unbuilt)

 dense_22 (Dense)                  ?                                      0␣
↪(unbuilt)


 Total params: 0 (0.00 B)

 Trainable params: 0 (0.00 B)

 Non-trainable params: 0 (0.00 B)

Epoch 1/10
125/125              2s 7ms/step -
acc: 0.5095 - loss: 0.6928 - val_acc: 0.5770 - val_loss: 0.6878
Epoch 2/10
125/125              1s 5ms/step -
acc: 0.7611 - loss: 0.6684 - val_acc: 0.6680 - val_loss: 0.6580
Epoch 3/10
```

```
125/125              1s 7ms/step -
acc: 0.8122 - loss: 0.5979 - val_acc: 0.7440 - val_loss: 0.5882
Epoch 4/10
125/125              1s 5ms/step -
acc: 0.8708 - loss: 0.4803 - val_acc: 0.7680 - val_loss: 0.5171
Epoch 5/10
125/125              1s 5ms/step -
acc: 0.8984 - loss: 0.3720 - val_acc: 0.7710 - val_loss: 0.4869
Epoch 6/10
125/125              1s 7ms/step -
acc: 0.9192 - loss: 0.2925 - val_acc: 0.8000 - val_loss: 0.4365
Epoch 7/10
125/125              1s 8ms/step -
acc: 0.9413 - loss: 0.2323 - val_acc: 0.8180 - val_loss: 0.4193
Epoch 8/10
125/125              1s 7ms/step -
acc: 0.9561 - loss: 0.1868 - val_acc: 0.8150 - val_loss: 0.4088
Epoch 9/10
125/125              1s 5ms/step -
acc: 0.9773 - loss: 0.1385 - val_acc: 0.8170 - val_loss: 0.4069
Epoch 10/10
125/125              2s 7ms/step -
acc: 0.9838 - loss: 0.1104 - val_acc: 0.8250 - val_loss: 0.4096
```

[58]:

```
a_c_c2 = hist_2.history['acc']
val_a_c_c2 = hist_2.history['val_acc']
lssTr_ain2 = hist_2.history['loss']
lssVal2 = hist_2.history['val_loss']

_epochs = range(1, len(a_c_c2) + 1)

pl.plot(_epochs, a_c_c2, color="cyan", linestyle="-", marker="o",␣
 ↪label="Training Accuracy")
pl.plot(_epochs, val_a_c_c2, color="magenta", linestyle="--", marker="s",␣
 ↪label="Validation Accuracy")
pl.title("Training and Validation Accuracy", fontsize=14, fontweight='bold')
pl.xlabel("Epochs")
pl.ylabel("Accuracy")
pl.legend(loc="lower right")
pl.grid(alpha=0.7)

pl.figure()


pl.plot(_epochs, lssTr_ain2, color="green", linestyle=":", marker="d",␣
 ↪label="Training Loss")
```

```
pl.plot(_epochs, lssVal2, color="orange", linestyle="-.", marker="^",␣
↪label="Validation Loss")
pl.title("Training and Validation Loss", fontsize=14, fontweight='bold')
pl.xlabel("Epochs")
pl.ylabel("Loss")
pl.legend(loc="upper right")
pl.grid(alpha=0.7)

pl.show()
```



[59]:
```
tst_lss2, test_a_c_c2 = mdl2.evaluate(XTesting, YTesting)
print('Test loss:', tst_lss2)
print('Test accuracy:', test_a_c_c2)
```

```
782/782               1s 1ms/step -
acc: 0.8335 - loss: 0.3740
Test loss: 0.37439119815826416
Test accuracy: 0.8318399786949158
```

custom-trained embedding layer with training sample size = 1000

[60]:
```
Fe_ature = 10000
_leng = 150

(TrainingX, TrainingY), (XTesting, YTesting) = imdb.
  ↪load_data(num_words=Fe_ature)

TrainingX = pad_sequences(TrainingX, maxlen=_leng)
XTesting = pad_sequences(XTesting, maxlen=_leng)
```

```
t_ext_ = np.concatenate((TrainingX, XTesting), axis=0)
lbl_s = np.concatenate((TrainingY, YTesting), axis=0)

TrainingX = TrainingX[:1000]
TrainingY = TrainingY[:1000]
```

[61]:
```
model3 = Sequential()
model3.add(Embedding(10000, 8, input_length=_leng))
model3.add(Flatten())
model3.add(Dense(1, activation='sigmoid'))
model3.compile(optimizer='rmsprop', loss='binary_crossentropy', metrics=['acc'])
model3.summary()
history3 = model3.fit(TrainingX, TrainingY,
                    epochs=10,
                    batch_size=32,
                    validation_split=0.2)
```

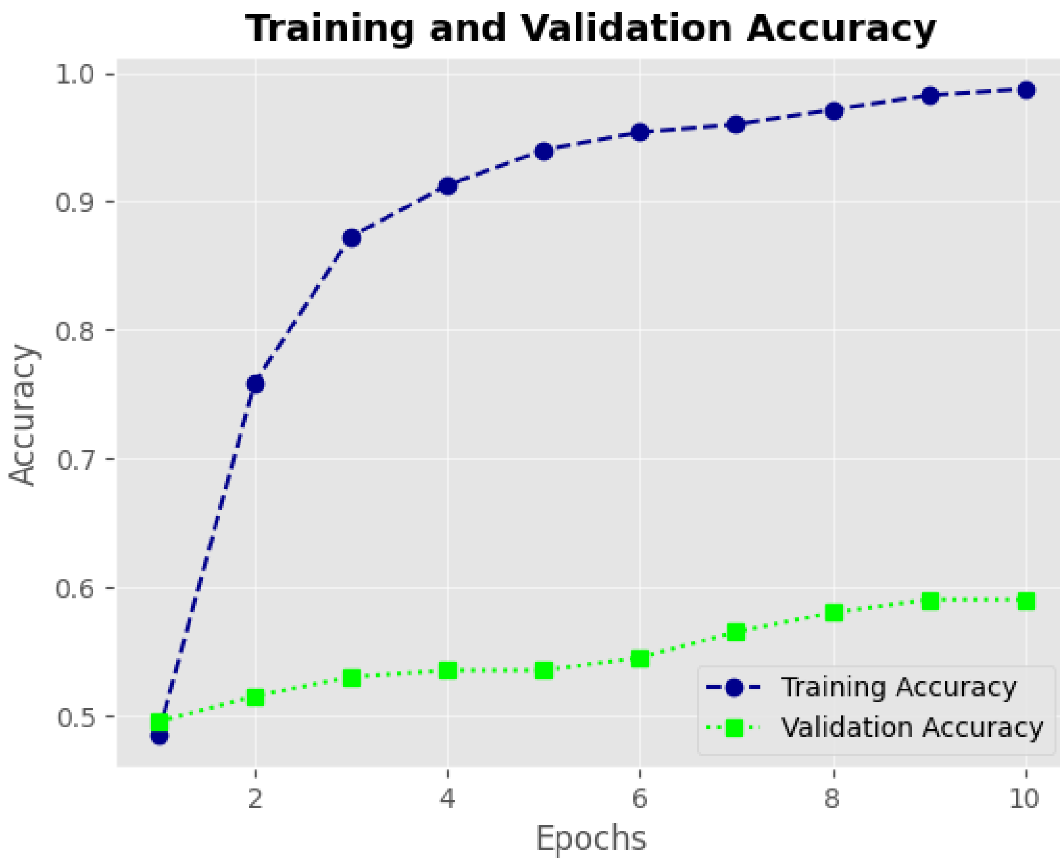
```
Model: "sequential_17"


 Layer (type)                          Output Shape                         ␣
↪Param #

 embedding_20 (Embedding)              ?                                 0␣
↪(unbuilt)

 flatten_15 (Flatten)                  ?                                 0␣
↪(unbuilt)

 dense_23 (Dense)                      ?                                 0␣
↪(unbuilt)


 Total params: 0 (0.00 B)

 Trainable params: 0 (0.00 B)

 Non-trainable params: 0 (0.00 B)

Epoch 1/10
25/25                 1s 11ms/step - acc:
0.4659 - loss: 0.6940 - val_acc: 0.4950 - val_loss: 0.6925
Epoch 2/10
25/25                 0s 4ms/step - acc:
0.7720 - loss: 0.6771 - val_acc: 0.5150 - val_loss: 0.6917
```

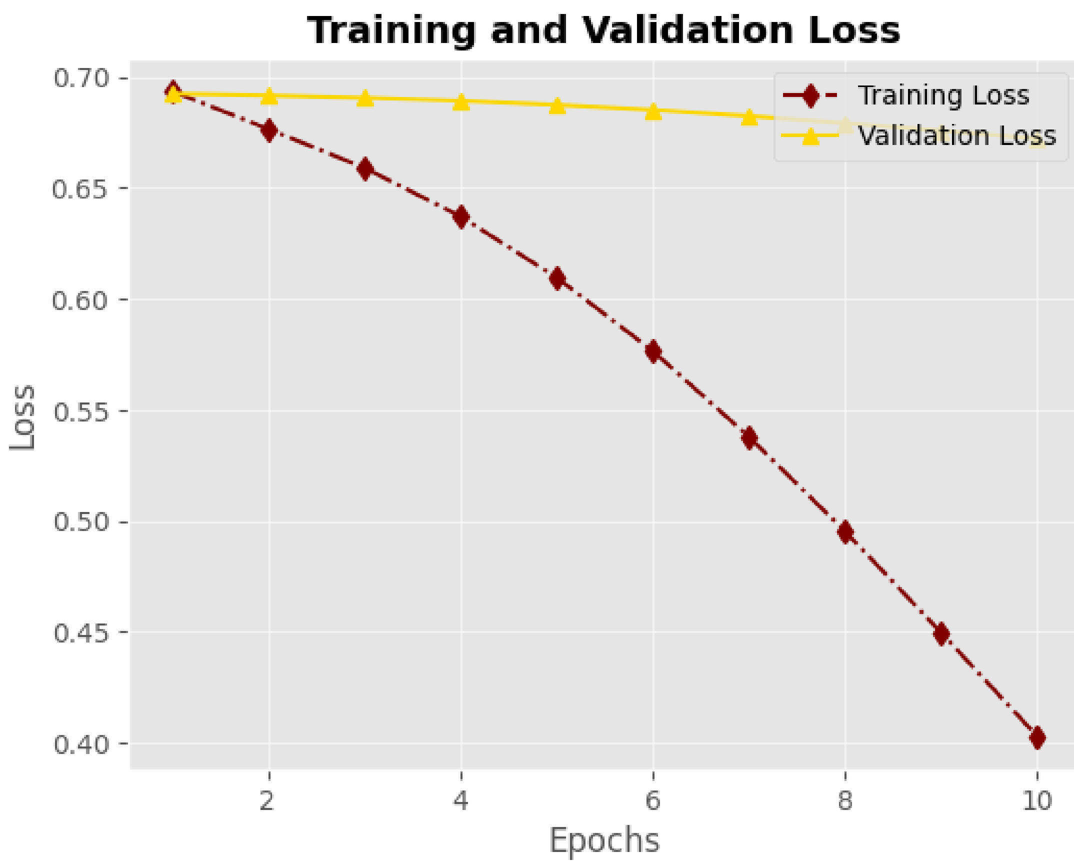
```
Epoch 3/10
25/25            0s 4ms/step - acc:
0.8554 - loss: 0.6625 - val_acc: 0.5300 - val_loss: 0.6907
Epoch 4/10
25/25            0s 4ms/step - acc:
0.9020 - loss: 0.6385 - val_acc: 0.5350 - val_loss: 0.6893
Epoch 5/10
25/25            0s 4ms/step - acc:
0.9378 - loss: 0.6124 - val_acc: 0.5350 - val_loss: 0.6875
Epoch 6/10
25/25            0s 4ms/step - acc:
0.9553 - loss: 0.5793 - val_acc: 0.5450 - val_loss: 0.6852
Epoch 7/10
25/25            0s 4ms/step - acc:
0.9606 - loss: 0.5437 - val_acc: 0.5650 - val_loss: 0.6824
Epoch 8/10
25/25            0s 4ms/step - acc:
0.9615 - loss: 0.5002 - val_acc: 0.5800 - val_loss: 0.6793
Epoch 9/10
25/25            0s 5ms/step - acc:
0.9806 - loss: 0.4551 - val_acc: 0.5900 - val_loss: 0.6758
Epoch 10/10
25/25            0s 7ms/step - acc:
0.9928 - loss: 0.4057 - val_acc: 0.5900 - val_loss: 0.6723
```

[62]:

```
a_c_c3 = history3.history["acc"]
val_a_c_c3 = history3.history["val_acc"]
lssTr_ain3 = history3.history["loss"]
lssVal3 = history3.history["val_loss"]

_epochs = range(1, len(a_c_c3) + 1)

pl.plot(_epochs, a_c_c3, color="darkblue", linestyle="--", marker="o",␣
 ↪label="Training Accuracy")
pl.plot(_epochs, val_a_c_c3, color="lime", linestyle=":", marker="s",␣
 ↪label="Validation Accuracy")
pl.title("Training and Validation Accuracy", fontsize=14, fontweight="bold")
pl.xlabel("Epochs")
pl.ylabel("Accuracy")
pl.legend(loc="lower right")
pl.grid(alpha=0.5)

pl.figure()


pl.plot(_epochs, lssTr_ain3, color="maroon", linestyle="-.", marker="d",␣
 ↪label="Training Loss")
```

```python
pl.plot(_epochs, lssVal3, color="gold", linestyle="-", marker="^", label="Validation Loss")
pl.title("Training and Validation Loss", fontsize=14, fontweight="bold")
pl.xlabel("Epochs")
pl.ylabel("Loss")
pl.legend(loc="upper right")
pl.grid(alpha=0.5)

pl.show()
```





[63]:
```
tst_lss3, tst_acc3 = model3.evaluate(XTesting, YTesting)
print('Test loss:', tst_lss3)
print('Test accuracy:', tst_acc3)
```

```
782/782              2s 2ms/step -
acc: 0.5724 - loss: 0.6780
Test loss: 0.6785645484924316
Test accuracy: 0.5690799951553345
```

custom-trained embedding layer with training sample size = 10000

[64]:
```
Fe_ature = 10000
_leng = 150

(TrainingX, TrainingY), (XTesting, YTesting) = imdb.
 ↪load_data(num_words=Fe_ature)

TrainingX = pad_sequences(TrainingX, maxlen=_leng)
XTesting = pad_sequences(XTesting, maxlen=_leng)
```

```
t_ext_ = np.concatenate((TrainingX, XTesting), axis=0)
lbl_s = np.concatenate((TrainingY, YTesting), axis=0)

TrainingX = TrainingX[:10000]
TrainingY = TrainingY[:10000]
```

[65]:
```
mdl4 = Sequential()
mdl4.add(Embedding(10000, 8, input_length=_leng))
mdl4.add(Flatten())
mdl4.add(Dense(1, activation='sigmoid'))
mdl4.compile(optimizer='rmsprop', loss='binary_crossentropy', metrics=['acc'])
mdl4.summary()
hist_4 = mdl4.fit(TrainingX, TrainingY,
                  epochs=10,
                  batch_size=32,
                  validation_split=0.2)
```

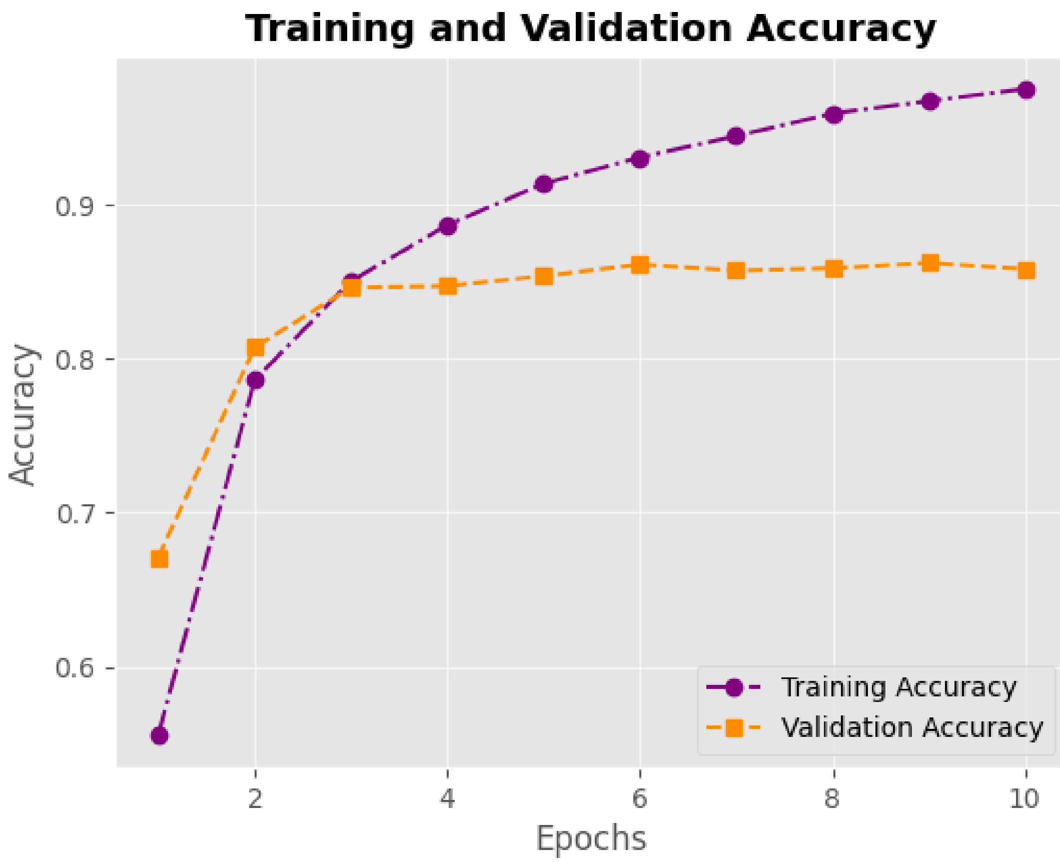
```
Model: "sequential_18"


 Layer (type)                         Output Shape                          ␣
↪Param #

 embedding_21 (Embedding)             ?                                   0␣
↪(unbuilt)

 flatten_16 (Flatten)                 ?                                   0␣
↪(unbuilt)

 dense_24 (Dense)                     ?                                   0␣
↪(unbuilt)


 Total params: 0 (0.00 B)


 Trainable params: 0 (0.00 B)


 Non-trainable params: 0 (0.00 B)

Epoch 1/10
250/250             2s 4ms/step -
acc: 0.5243 - loss: 0.6914 - val_acc: 0.6710 - val_loss: 0.6661
Epoch 2/10
250/250             1s 3ms/step -
acc: 0.7696 - loss: 0.6121 - val_acc: 0.8075 - val_loss: 0.4936
```

```
Epoch 3/10
250/250              1s 3ms/step -
acc: 0.8485 - loss: 0.4249 - val_acc: 0.8465 - val_loss: 0.3821
Epoch 4/10
250/250              1s 3ms/step -
acc: 0.8808 - loss: 0.3174 - val_acc: 0.8475 - val_loss: 0.3453
Epoch 5/10
250/250              1s 3ms/step -
acc: 0.9140 - loss: 0.2486 - val_acc: 0.8540 - val_loss: 0.3289
Epoch 6/10
250/250              1s 3ms/step -
acc: 0.9322 - loss: 0.2029 - val_acc: 0.8615 - val_loss: 0.3186
Epoch 7/10
250/250              1s 3ms/step -
acc: 0.9475 - loss: 0.1649 - val_acc: 0.8575 - val_loss: 0.3187
Epoch 8/10
250/250              1s 3ms/step -
acc: 0.9622 - loss: 0.1356 - val_acc: 0.8590 - val_loss: 0.3214
Epoch 9/10
250/250              1s 3ms/step -
acc: 0.9677 - loss: 0.1121 - val_acc: 0.8625 - val_loss: 0.3303
Epoch 10/10
250/250              2s 4ms/step -
acc: 0.9755 - loss: 0.0968 - val_acc: 0.8585 - val_loss: 0.3352
```

[66]:

```python
a_c_c4 = hist_4.history["acc"]
val_a_c_c4 = hist_4.history["val_acc"]
lssTr_ain4 = hist_4.history["loss"]
lssVal4 = hist_4.history["val_loss"]

_epochs = range(1, len(a_c_c4) + 1)

pl.plot(_epochs, a_c_c4, color="purple", linestyle="-.", marker="o",␣
 ↪label="Training Accuracy")
pl.plot(_epochs, val_a_c_c4, color="darkorange", linestyle="--", marker="s",␣
 ↪label="Validation Accuracy")
pl.title("Training and Validation Accuracy", fontsize=14, fontweight="bold")
pl.xlabel("Epochs")
pl.ylabel("Accuracy")
pl.legend(loc="lower right")
pl.grid(alpha=0.6)

pl.figure()


pl.plot(_epochs, lssTr_ain4, color="navy", linestyle="-", marker="^",␣
 ↪label="Training Loss")
```

```
pl.plot(_epochs, lssVal4, color="crimson", linestyle=":", marker="d",␣
  ↪label="Validation Loss")
pl.title("Training and Validation Loss", fontsize=14, fontweight="bold")
pl.xlabel("Epochs")
pl.ylabel("Loss")
pl.legend(loc="upper right")
pl.grid(alpha=0.6)

pl.show()
```



[67]:
```
tst_lss4, tst_a_c_c4 = mdl4.evaluate(XTesting, YTesting)
print('Test loss:', tst_lss4)
print('Test accuracy:', tst_a_c_c4)
```

```
782/782              2s 2ms/step -
acc: 0.8493 - loss: 0.3503
Test loss: 0.34741348028182983
Test accuracy: 0.8511199951171875
```

[68]:
```
!curl -O https://ai.stanford.edu/~amaas/data/sentiment/aclImdb_v1.tar.gz
!tar -xf aclImdb_v1.tar.gz
!rm -r aclImdb/train/unsup
```

```
  % Total    % Received % Xferd  Average Speed   Time    Time     Time  Current
                                 Dload  Upload   Total   Spent    Left  Speed
100 80.2M  100 80.2M    0     0  6057k      0  0:00:13  0:00:13 --:--:-- 6677k
```

[69]:
```
import os
import shutil
```

```
imdb = 'aclImdb'
training = os.path.join(imdb, 'train')

lbl_s = []
t_ext_ = []

for label_type in ['neg', 'pos']:
    dir_path = os.path.join(training, label_type)  # Updated variable name to␣
 ↪dir_path
    for fname in os.listdir(dir_path):
        if fname.endswith('.txt'):
            with open(os.path.join(dir_path, fname), encoding='utf-8') as f:
                t_ext_.append(f.read())
            if label_type == 'neg':
                lbl_s.append(0)  # Negative label
            else:
                lbl_s.append(1)  # Positive label
```

Utilizing Trained Word Embeds If there is not enough training data to obtain word embeddings along with the problem you wish to solve, you can use pretrained word embeddings.

Tokenizing the data

[70]:
```
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
import numpy as np

_leng = 150  # Cut off review after 150 words
dataTrain = 100  # Training sample 100
dataVaild = 10000  # Validation sample 10000
wrds = 10000  # Considers only the top 10000 words in the dataset

tkn1 = Tokenizer(num_words=wrds)
tkn1.fit_on_texts(t_ext_)
seq_uen_ce = tkn1.texts_to_sequences(t_ext_)
wrd_idx = tkn1.word_index
print("Found %s unique tokens." % len(wrd_idx))

_da_ta = pad_sequences(seq_uen_ce, maxlen=_leng)

lbl_s = np.asarray(lbl_s)
print("Shape of data tensor:", _da_ta.shape)
print("Shape of label tensor:", lbl_s.shape)

# Split data into training and validation set, but shuffle it, since samples␣
 ↪are ordered:
# all negatives first, then all positives
ind_icess = np.arange(_da_ta.shape[0])
```

```
np.random.shuffle(ind_icess)
_da_ta = _da_ta[ind_icess]
lbl_s = lbl_s[ind_icess]

TrainingX = _da_ta[:dataTrain]
TrainingY = lbl_s[:dataTrain]
X_Valid_ation = _da_ta[dataTrain:dataTrain+dataVaild]
Y_Valid_ation = lbl_s[dataTrain:dataTrain+dataVaild]
```

```
Found 88582 unique tokens.
Shape of data tensor: (25000, 150)
Shape of label tensor: (25000,)
```

Installing and setting up the GloVe word embedding

[71]:
```
import numpy as np
import requests
from io import BytesIO
import zipfile

glURL = 'https://nlp.stanford.edu/data/glove.6B.zip'
glZIP = requests.get(glURL)


with zipfile.ZipFile(BytesIO(glZIP.content)) as z:
    z.extractall('/content/glove')

# Loading GloVe embeddings into memory
embdIdx = {}
with open('/content/glove/glove.6B.100d.txt', encoding='utf-8') as f:
    for line in f:
        values = line.split()
        word = values[0]
        coefs = np.asarray(values[1:], dtype='float32')
        embdIdx[word] = coefs

print("Found %s word vectors." % len(embdIdx))
```

```
Found 400000 word vectors.
```

Preparing the GloVe word embeddings matrix

pretrained word embedding layer with training sample size = 100

[72]:
```
emb_d = 100

emb_mat = np.zeros((wrds, emb_d))
for word, i in wrd_idx.items():
    embdVector = embdIdx.get(word)
```

```
    if i < wrds:
        if embdVector is not None:
            emb_mat[i] = embdVector
```

[73]:
```
from keras.models import Sequential
from keras.layers import Embedding, Flatten, Dense

mdl = Sequential()
mdl.add(Embedding(wrds, emb_d, input_length=_leng))
mdl.add(Flatten())
mdl.add(Dense(32, activation='relu'))
mdl.add(Dense(1, activation='sigmoid'))
mdl.summary()
```

```
Model: "sequential_19"


 Layer (type)                    Output Shape                              ␣
↪Param #

 embedding_22 (Embedding)        ?                                       0␣
↪(unbuilt)

 flatten_17 (Flatten)            ?                                       0␣
↪(unbuilt)

 dense_25 (Dense)                ?                                       0␣
↪(unbuilt)

 dense_26 (Dense)                ?                                       0␣
↪(unbuilt)


 Total params: 0 (0.00 B)

 Trainable params: 0 (0.00 B)

 Non-trainable params: 0 (0.00 B)
```

[74]:
```
from tensorflow.keras.layers import Embedding
from tensorflow.keras.models import Sequential
from tensorflow.keras.initializers import Constant

embdDim = emb_mat.shape[1]
```

```
SizeV_ocab = emb_mat.shape[0]


mdl = Sequential()
mdl.add(
    Embedding(
        input_dim=SizeV_ocab,
        output_dim=embdDim,
        embeddings_initializer=Constant(emb_mat),
        input_length=_leng,
        trainable=False
    )
)


mdl.summary()
```

Model: "sequential_20"

```
 Layer (type)                          Output Shape                         ␣
↪Param #

 embedding_23 (Embedding)              ?                                  0␣
↪(unbuilt)
```

Total params: 0 (0.00 B)

Trainable params: 0 (0.00 B)

Non-trainable params: 0 (0.00 B)

[75]:
```
from tensorflow.keras.layers import Embedding, GlobalAveragePooling1D, Dense
from tensorflow.keras.models import Sequential
from tensorflow.keras.initializers import Constant

embdDim = emb_mat.shape[1]
SizeV_ocab = emb_mat.shape[0]

# Define the model
mdl = Sequential()
mdl.add(
    Embedding(
```

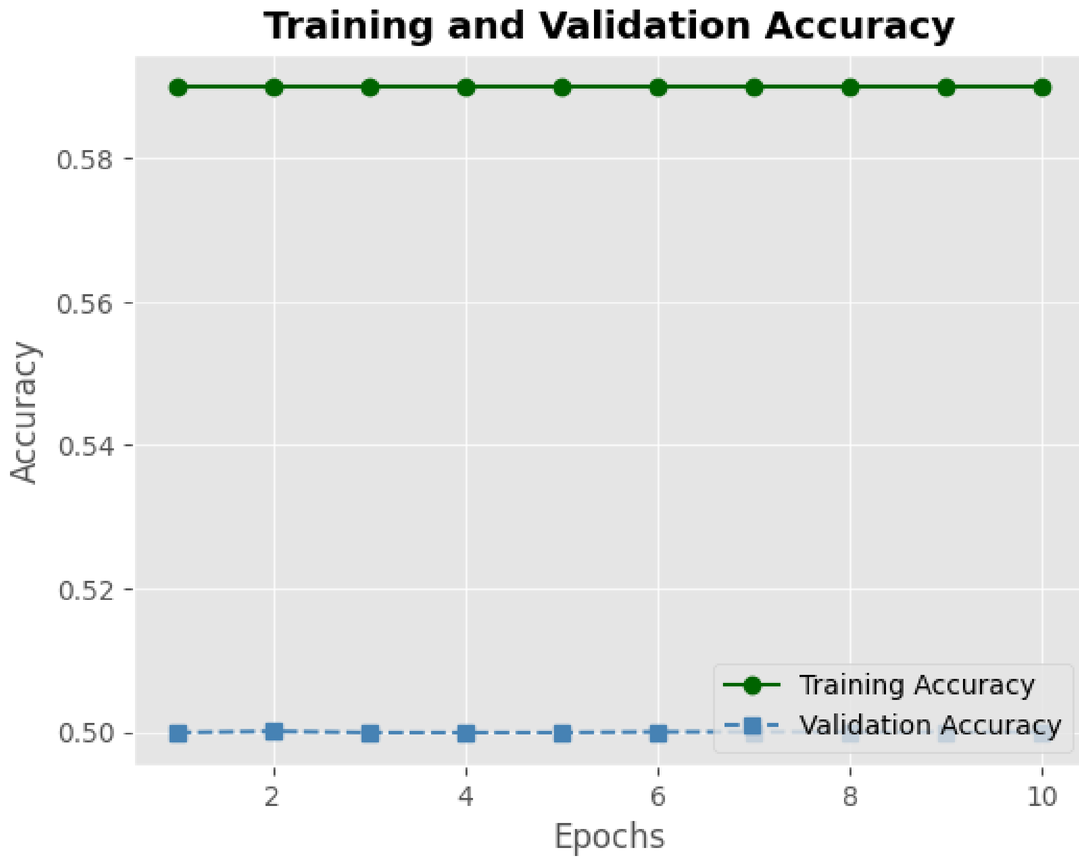
```
        input_dim=SizeV_ocab,
        output_dim=embdDim,
        embeddings_initializer=Constant(emb_mat),
        input_length=_leng,
        trainable=False
    )
)
mdl.add(GlobalAveragePooling1D())
mdl.add(Dense(1, activation='sigmoid'))  # Final output layer for binary␣
 ↪classification

# Compile and fit the model
mdl.compile(optimizer='rmsprop', loss='binary_crossentropy', metrics=['acc'])
_hist = mdl.fit(
    TrainingX, TrainingY,
    epochs=10,
    batch_size=32,
    validation_data=(X_Valid_ation, Y_Valid_ation)
)

# Save the model weights
mdl.save_weights('pre_trained_glove_model.weights.h5')
```

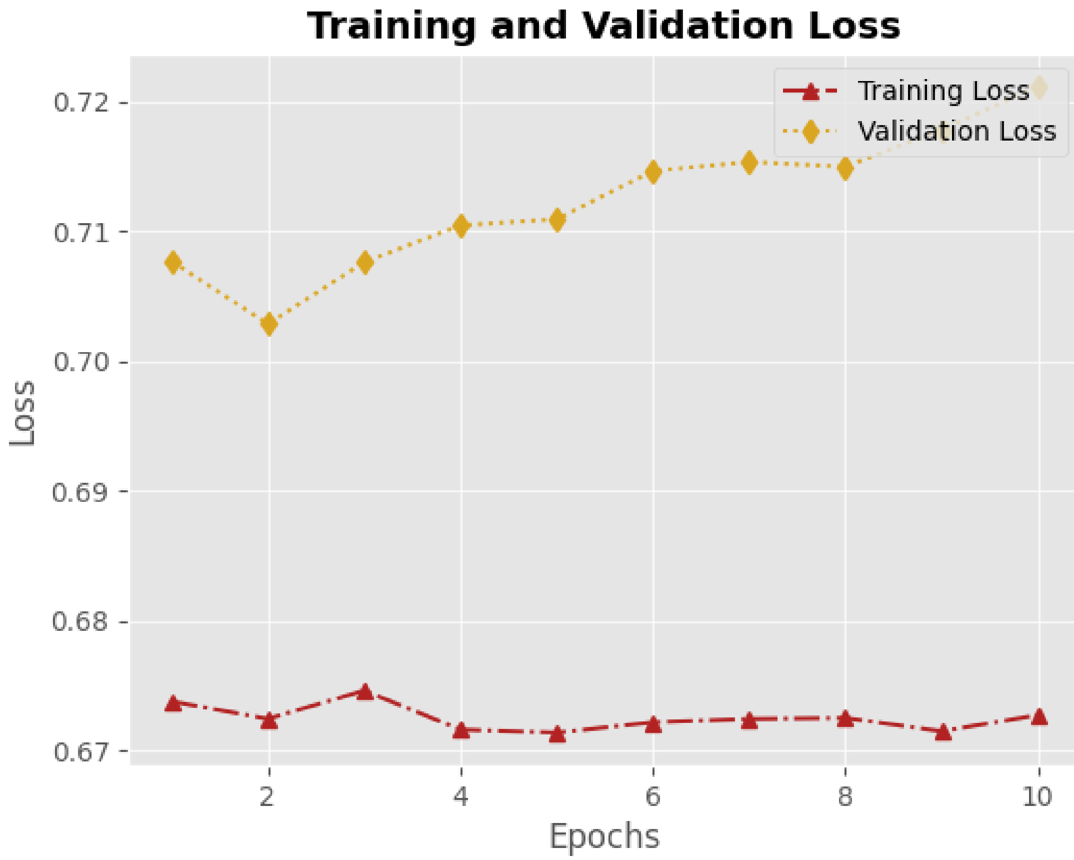
```
Epoch 1/10
4/4               2s 202ms/step - acc:
0.5777 - loss: 0.6739 - val_acc: 0.4999 - val_loss: 0.7077
Epoch 2/10
4/4               0s 151ms/step - acc:
0.6110 - loss: 0.6647 - val_acc: 0.5001 - val_loss: 0.7029
Epoch 3/10
4/4               1s 431ms/step - acc:
0.6277 - loss: 0.6603 - val_acc: 0.4999 - val_loss: 0.7076
Epoch 4/10
4/4               3s 440ms/step - acc:
0.6006 - loss: 0.6663 - val_acc: 0.4999 - val_loss: 0.7104
Epoch 5/10
4/4               3s 436ms/step - acc:
0.5839 - loss: 0.6739 - val_acc: 0.4999 - val_loss: 0.7109
Epoch 6/10
4/4               1s 296ms/step - acc:
0.5568 - loss: 0.6853 - val_acc: 0.5000 - val_loss: 0.7147
Epoch 7/10
4/4               1s 278ms/step - acc:
0.6027 - loss: 0.6662 - val_acc: 0.5000 - val_loss: 0.7153
Epoch 8/10
4/4               1s 272ms/step - acc:
0.5402 - loss: 0.6920 - val_acc: 0.5000 - val_loss: 0.7150
```

```
Epoch 9/10
4/4              1s 436ms/step - acc:
0.5725 - loss: 0.6758 - val_acc: 0.5000 - val_loss: 0.7178
Epoch 10/10
4/4              2s 146ms/step - acc:
0.5412 - loss: 0.6920 - val_acc: 0.5000 - val_loss: 0.7212
```

The Embeddig layer receives pre-trained word embedding. Setting this to False when calling the Embedding layer guarantees that it cannot be trained. Setting trainable = True will allow the optimization procedure to alter the word embedding settings. To keep students from forgetting what they already "know," it is advisable to avoid updating pretrained parts while they are still receiving instruction.

[76]:
```python
import matplotlib.pyplot as pl

accuracyValue = _hist.history['acc']
valid_accuracyValue = _hist.history['val_acc']
train_lossValue = _hist.history['loss']
valid_lossValue = _hist.history['val_loss']

epochs = range(1, len(accuracyValue) + 1)

pl.plot(epochs, accuracyValue, color="darkgreen", linestyle="-", marker="o",␣
 ↪label="Training Accuracy")
pl.plot(epochs, valid_accuracyValue, color="steelblue", linestyle="--",␣
 ↪marker="s", label="Validation Accuracy")
pl.title("Training and Validation Accuracy", fontsize=14, fontweight="bold")
pl.xlabel("Epochs")
pl.ylabel("Accuracy")
pl.legend(loc="lower right")
pl.grid(alpha=0.7)

pl.figure()


pl.plot(epochs, train_lossValue, color="firebrick", linestyle="-.", marker="^",␣
 ↪label="Training Loss")
pl.plot(epochs, valid_lossValue, color="goldenrod", linestyle=":", marker="d",␣
 ↪label="Validation Loss")
pl.title("Training and Validation Loss", fontsize=14, fontweight="bold")
pl.xlabel("Epochs")
pl.ylabel("Loss")
pl.legend(loc="upper right")
pl.grid(alpha=0.7)

pl.show()
```


Training and Validation Accuracy
0.58
0.56
0.54
0.52
0.50
Accuracy
2
4
6
8
10
Epochs
Training Accuracy
Validation Accuracy



pretrained word embedding layer with training sample size = 5000

[77]:
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding, Flatten, Dense

mdl11 = Sequential()
mdl11.add(Embedding(SizeV_ocab, embdDim, input_length=_leng))
mdl11.add(Flatten())
mdl11.add(Dense(32, activation='relu'))
mdl11.add(Dense(1, activation='sigmoid'))

mdl11.build(input_shape=(None, _leng))

# Load pretrained weights
mdl11.layers[0].set_weights([emb_mat])
mdl11.layers[0].trainable = False


mdl11.compile(optimizer='rmsprop', loss='binary_crossentropy', metrics=['acc'])
_hist11 = mdl11.fit(
```

```
    TrainingX, TrainingY,
    epochs=10,
    batch_size=32,
    validation_data=(X_Valid_ation, Y_Valid_ation)
)

# Save the model weights
mdl11.save_weights('pre_trained_glove_model.weights.h5')
```

```
Epoch 1/10
4/4               2s 279ms/step - acc:
0.4175 - loss: 3.1180 - val_acc: 0.5368 - val_loss: 0.6941
Epoch 2/10
4/4               1s 204ms/step - acc:
0.8937 - loss: 0.3812 - val_acc: 0.5304 - val_loss: 0.7019
Epoch 3/10
4/4               1s 221ms/step - acc:
0.9845 - loss: 0.2223 - val_acc: 0.5002 - val_loss: 2.2073
Epoch 4/10
4/4               1s 236ms/step - acc:
0.5595 - loss: 1.0180 - val_acc: 0.5003 - val_loss: 1.2357
Epoch 5/10
4/4               1s 224ms/step - acc:
0.9845 - loss: 0.1504 - val_acc: 0.5125 - val_loss: 0.8945
Epoch 6/10
4/4               1s 220ms/step - acc:
1.0000 - loss: 0.0646 - val_acc: 0.5026 - val_loss: 1.0193
Epoch 7/10
4/4               1s 221ms/step - acc:
1.0000 - loss: 0.0517 - val_acc: 0.5555 - val_loss: 0.7347
Epoch 8/10
4/4               1s 435ms/step - acc:
1.0000 - loss: 0.0387 - val_acc: 0.5041 - val_loss: 1.0658
Epoch 9/10
4/4               1s 443ms/step - acc:
1.0000 - loss: 0.0242 - val_acc: 0.5554 - val_loss: 0.7406
Epoch 10/10
4/4               1s 444ms/step - acc:
1.0000 - loss: 0.0240 - val_acc: 0.5207 - val_loss: 0.9704
```

[78]:
```
tst_lss11, tst_a_c_c11 = mdl11.evaluate(XTesting, YTesting)
print('Test loss:', tst_lss11)
print('Test accuracy:', tst_a_c_c11)
```

```
782/782               4s 5ms/step -
acc: 0.4928 - loss: 1.0969
Test loss: 1.0798628330230713
Test accuracy: 0.5009599924087524
```

pretrained word embedding layer with training sample size = 1000

[79]:
```
import numpy as np

_leng = 150  # Cut off review after 150 words
dataTrain = 1000  # Trains on 1000 samples
dataVaild = 10000  # Validation sample 10000
wrds = 10000  # Considers only the top 10000 words in the dataset

tokenizer3 = Tokenizer(num_words=wrds)
tokenizer3.fit_on_texts(t_ext_)
sequences = tokenizer3.texts_to_sequences(t_ext_)
wrd_idx = tokenizer3.word_index
print("Found %s unique tokens." % len(wrd_idx))

_da_ta = pad_sequences(sequences, maxlen=_leng)

lbl_s = np.asarray(lbl_s)
print("Shape of data tensor:", _da_ta.shape)
print("Shape of label tensor:", lbl_s.shape)

indices = np.arange(_da_ta.shape[0])
np.random.shuffle(indices)
_da_ta = _da_ta[indices]
lbl_s = lbl_s[indices]

TrainingX = _da_ta[:dataTrain]
TrainingY = lbl_s[:dataTrain]
X_Valid_ation = _da_ta[dataTrain:dataTrain+dataVaild]
Y_Valid_ation = lbl_s[dataTrain:dataTrain+dataVaild]

emb_d = 100

emb_mat = np.zeros((wrds, emb_d))
for word, i in wrd_idx.items():
    embdVector = embdIdx.get(word)
    if i < wrds:
        if embdVector is not None:
            emb_mat[i] = embdVector


mdl12 = Sequential()
mdl12.add(Embedding(wrds, emb_d, input_length=_leng))
mdl12.add(Flatten())
mdl12.add(Dense(32, activation='relu'))
mdl12.add(Dense(1, activation='sigmoid'))
mdl12.summary()
```

```
mdl12.layers[0].build(input_shape=(None, _leng))

# Set the pre-trained embedding matrix as weights
mdl12.layers[0].set_weights([emb_mat])
mdl12.layers[0].trainable = False

# Compile the model
mdl12.compile(optimizer='rmsprop',
              loss='binary_crossentropy',
              metrics=['acc'])


hist_12 = mdl12.fit(
    TrainingX, TrainingY,
    epochs=10,
    batch_size=32,
    validation_data=(X_Valid_ation, Y_Valid_ation)
)
mdl12.save_weights('pre_trained_glove_model.weights.h5')


a_c_c = hist_12.history['acc']
val_a_c_c = hist_12.history['val_acc']
lssTr_ain12 = hist_12.history['loss']
lssVal12 = hist_12.history['val_loss']

_epochs = range(1, len(a_c_c) + 1)

pl.plot(_epochs, a_c_c, color="teal", linestyle="--", marker="o",␣
 ↪label="Training Accuracy")
pl.plot(_epochs, val_a_c_c, color="darkorange", linestyle="-.", marker="s",␣
 ↪label="Validation Accuracy")
pl.title("Training and Validation Accuracy", fontsize=16, fontweight="bold")
pl.xlabel("Epochs")
pl.ylabel("Accuracy")
pl.legend(loc="lower right", fontsize=12)
pl.grid(alpha=0.6)

pl.figure()


pl.plot(_epochs, lssTr_ain12, color="navy", linestyle=":", marker="d",␣
 ↪label="Training Loss")
pl.plot(_epochs, lssVal12, color="crimson", linestyle="-", marker="^",␣
 ↪label="Validation Loss")
```

```
pl.title("Training and Validation Loss", fontsize=16, fontweight="bold")
pl.xlabel("Epochs")
pl.ylabel("Loss")
pl.legend(loc="upper right", fontsize=12)
pl.grid(alpha=0.6)

pl.show()
```

```
Found 88582 unique tokens.
Shape of data tensor: (25000, 150)
Shape of label tensor: (25000,)
```

Model: "sequential_23"

```
 Layer (type)                          Output Shape                          ␣
↪Param #

 embedding_26 (Embedding)              ?                                   0␣
↪(unbuilt)

 flatten_19 (Flatten)                  ?                                   0␣
↪(unbuilt)

 dense_30 (Dense)                      ?                                   0␣
↪(unbuilt)

 dense_31 (Dense)                      ?                                   0␣
↪(unbuilt)
```

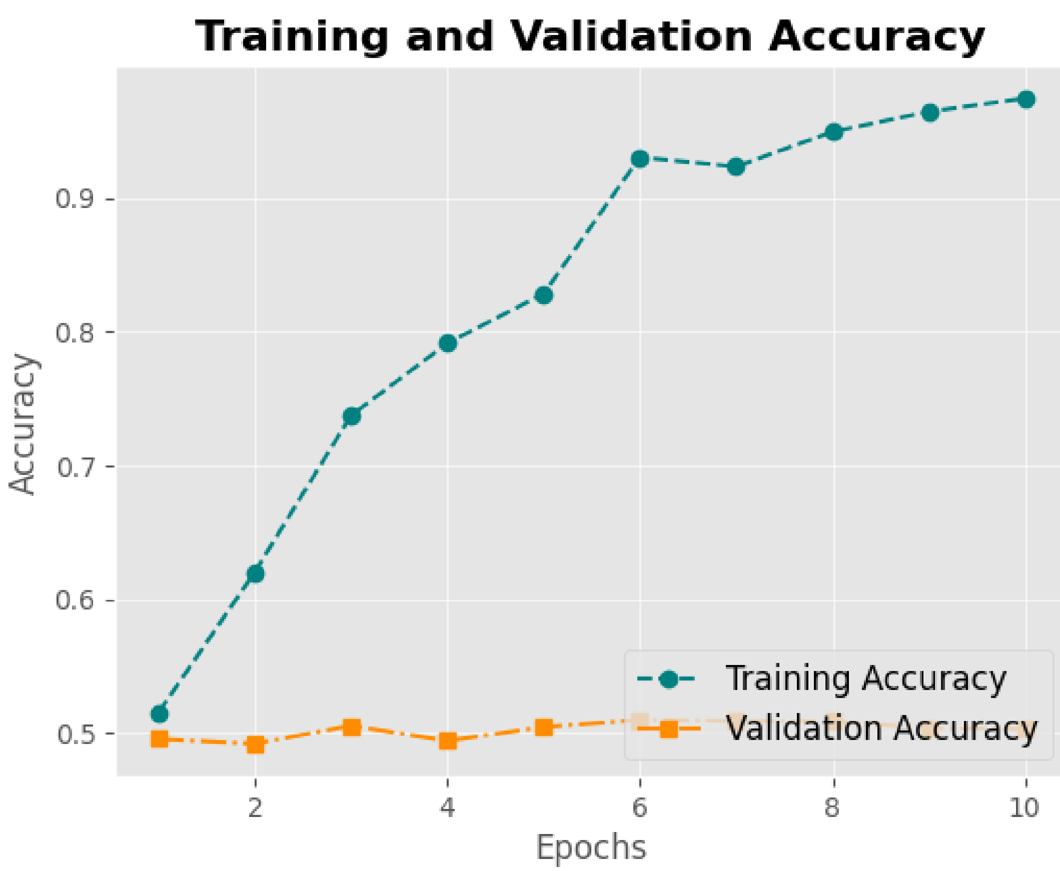
Total params: 0 (0.00 B)

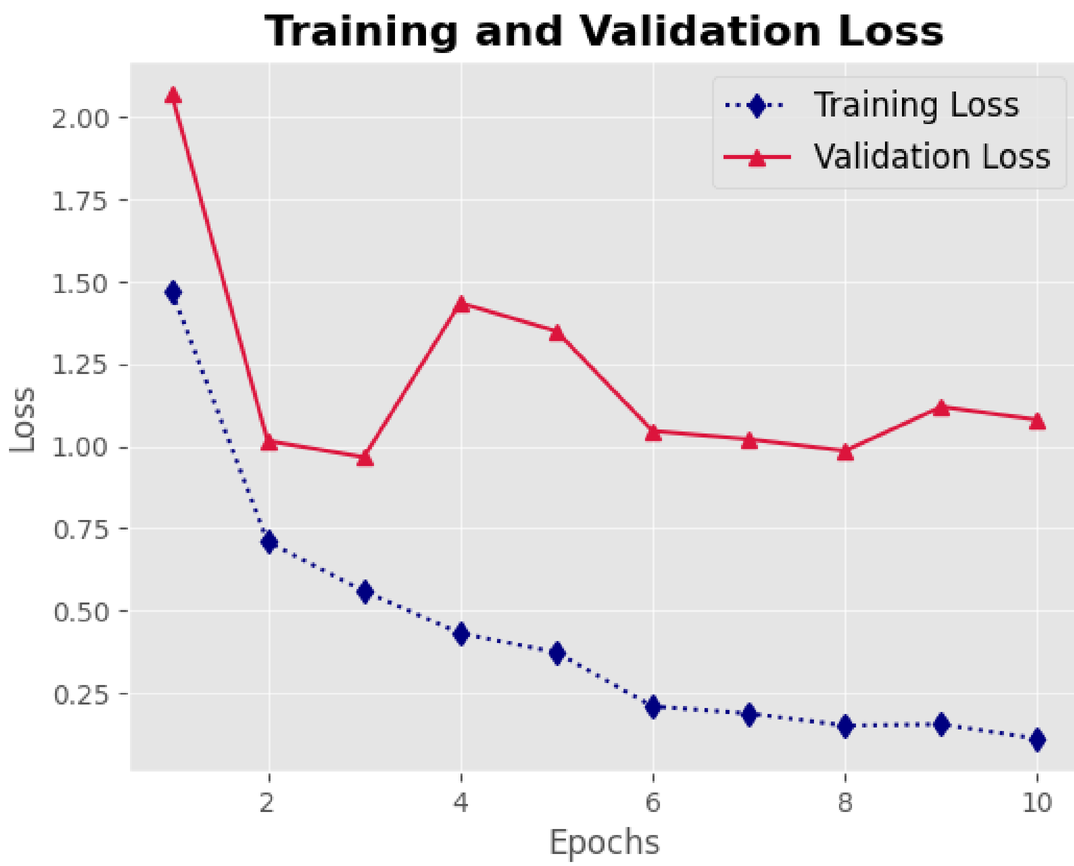
Trainable params: 0 (0.00 B)

Non-trainable params: 0 (0.00 B)

```
Epoch 1/10
32/32              3s 55ms/step - acc:
0.5253 - loss: 2.0360 - val_acc: 0.4955 - val_loss: 2.0731
Epoch 2/10
32/32              2s 52ms/step - acc:
0.6140 - loss: 0.7272 - val_acc: 0.4920 - val_loss: 1.0154
Epoch 3/10
32/32              3s 52ms/step - acc:
```

```
0.7016 - loss: 0.5916 - val_acc: 0.5054 - val_loss: 0.9662
Epoch 4/10
32/32                2s 59ms/step - acc:
0.7743 - loss: 0.4390 - val_acc: 0.4942 - val_loss: 1.4355
Epoch 5/10
32/32                2s 52ms/step - acc:
0.8700 - loss: 0.3115 - val_acc: 0.5044 - val_loss: 1.3494
Epoch 6/10
32/32                3s 52ms/step - acc:
0.9107 - loss: 0.2226 - val_acc: 0.5097 - val_loss: 1.0459
Epoch 7/10
32/32                1s 31ms/step - acc:
0.9003 - loss: 0.2228 - val_acc: 0.5090 - val_loss: 1.0205
Epoch 8/10
32/32                1s 28ms/step - acc:
0.9478 - loss: 0.1540 - val_acc: 0.5087 - val_loss: 0.9854
Epoch 9/10
32/32                1s 27ms/step - acc:
0.9790 - loss: 0.1054 - val_acc: 0.5037 - val_loss: 1.1193
Epoch 10/10
32/32                1s 29ms/step - acc:
0.9952 - loss: 0.0419 - val_acc: 0.5030 - val_loss: 1.0798
```





[80]:
```
tst_lss12, tst_a_c_c12 = mdl12.evaluate(XTesting, YTesting)

print('Test loss:', tst_lss12)
print('Test accuracy:', tst_a_c_c12)
```

```
782/782              2s 2ms/step -
acc: 0.4950 - loss: 1.0939
Test loss: 1.0987735986709595
Test accuracy: 0.4942399859428406
```

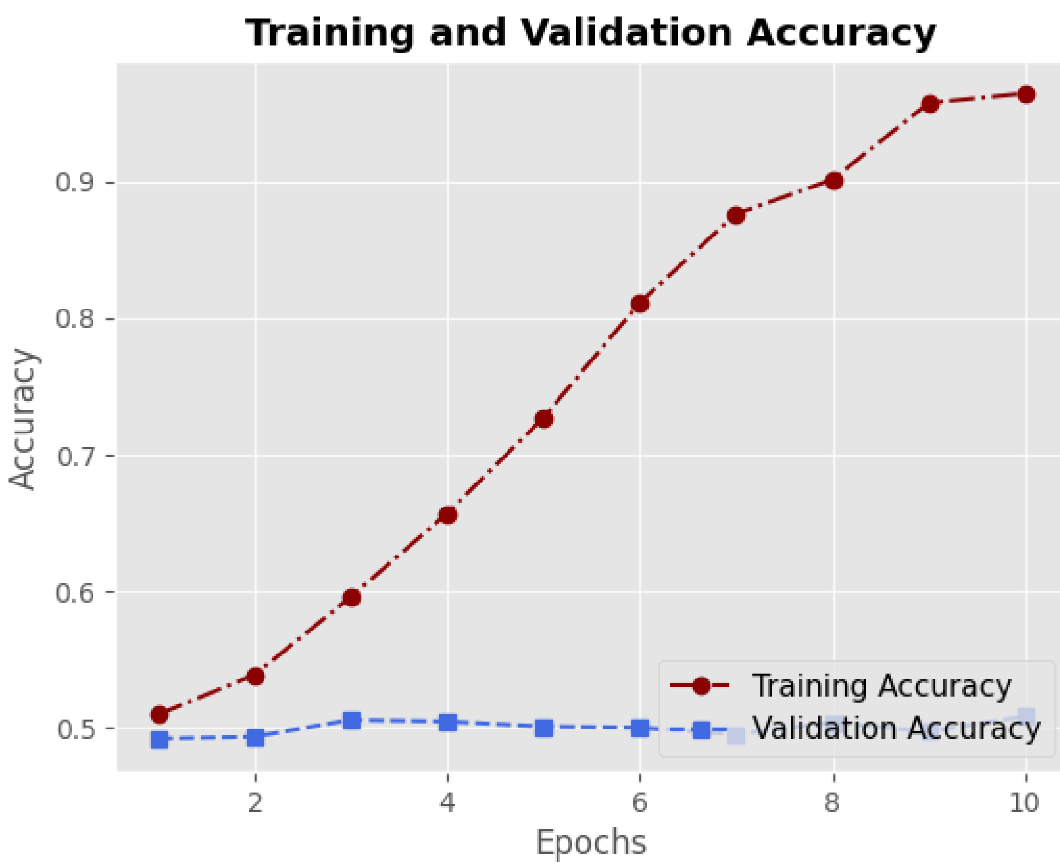
[81]:
```
mdl13 = Sequential()
mdl13.add(Embedding(wrds, emb_d, input_length=_leng))
mdl13.add(Flatten())
mdl13.add(Dense(32, activation='relu'))
mdl13.add(Dense(1, activation='sigmoid'))
mdl13.summary()
```

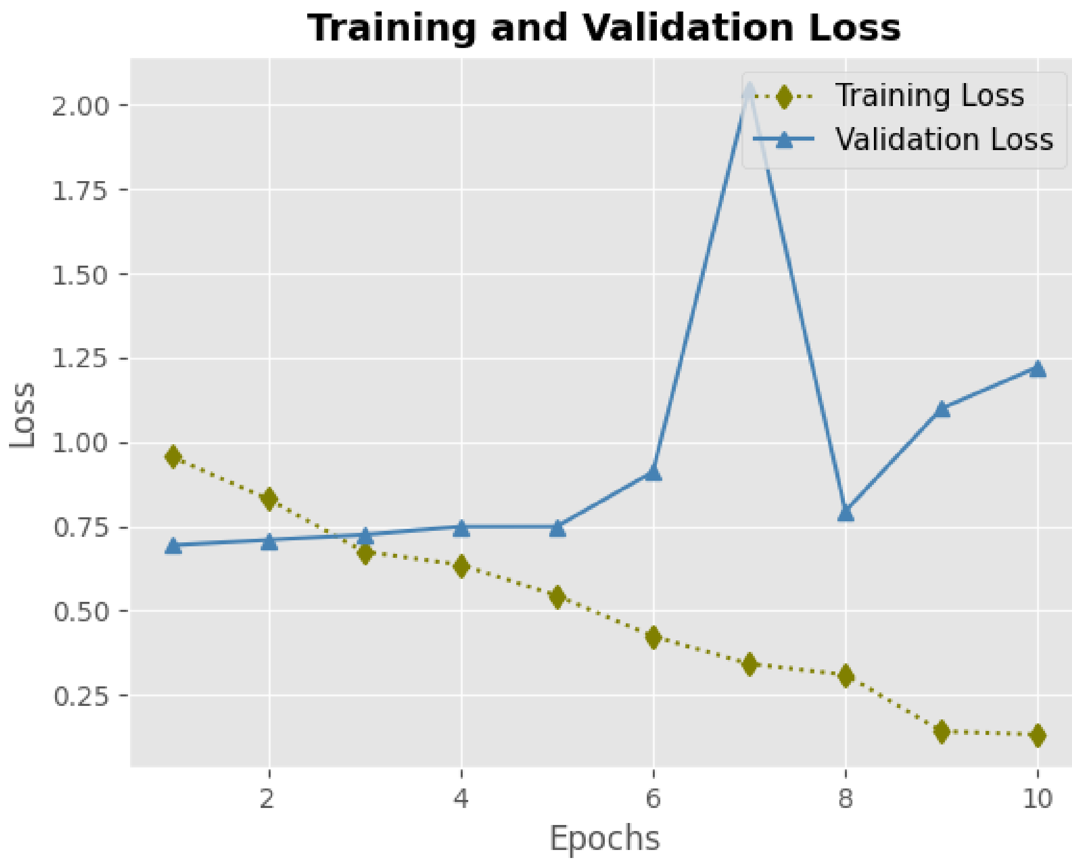
```
mdl13.layers[0].build(input_shape=(None, _leng))
mdl13.layers[0].set_weights([emb_mat])
mdl13.layers[0].trainable = False


mdl13.compile(optimizer='rmsprop',
              loss='binary_crossentropy',
              metrics=['acc'])


hist_13 = mdl13.fit(
    TrainingX, TrainingY,
    epochs=10,
    batch_size=32,
    validation_data=(X_Valid_ation, Y_Valid_ation)
)


mdl13.save_weights('pre_trained_glove_model.weights.h5')


import matplotlib.pyplot as pl

a_c_c13 = hist_13.history['acc']
val_a_c_c13 = hist_13.history['val_acc']
lssTr_ain13 = hist_13.history['loss']
lssVal13 = hist_13.history['val_loss']

_epochs = range(1, len(a_c_c13) + 1)

pl.plot(_epochs, a_c_c13, color="darkred", linestyle="-.", marker="o",␣
 ↪label="Training Accuracy")
pl.plot(_epochs, val_a_c_c13, color="royalblue", linestyle="--", marker="s",␣
 ↪label="Validation Accuracy")
pl.title("Training and Validation Accuracy", fontsize=14, fontweight="bold")
pl.xlabel("Epochs")
pl.ylabel("Accuracy")
pl.legend(loc="lower right", fontsize=11)
pl.grid(alpha=0.8)

pl.figure()


pl.plot(_epochs, lssTr_ain13, color="olive", linestyle=":", marker="d",␣
 ↪label="Training Loss")
```

```
pl.plot(_epochs, lssVal13, color="steelblue", linestyle="-", marker="^",␣
 ↪label="Validation Loss")
pl.title("Training and Validation Loss", fontsize=14, fontweight="bold")
pl.xlabel("Epochs")
pl.ylabel("Loss")
pl.legend(loc="upper right", fontsize=11)
pl.grid(alpha=0.8)

pl.show()
```

```
Model: "sequential_24"


 Layer (type)                          Output Shape                         ␣
↪Param #

 embedding_27 (Embedding)              ?                                 0␣
↪(unbuilt)

 flatten_20 (Flatten)                  ?                                 0␣
↪(unbuilt)

 dense_32 (Dense)                      ?                                 0␣
↪(unbuilt)

 dense_33 (Dense)                      ?                                 0␣
↪(unbuilt)


 Total params: 0 (0.00 B)

 Trainable params: 0 (0.00 B)

 Non-trainable params: 0 (0.00 B)

Epoch 1/10
32/32                  2s 33ms/step - acc:
0.4838 - loss: 1.4032 - val_acc: 0.4923 - val_loss: 0.6933
Epoch 2/10
32/32                  1s 47ms/step - acc:
0.5365 - loss: 0.8295 - val_acc: 0.4939 - val_loss: 0.7093
Epoch 3/10
32/32                  2s 55ms/step - acc:
0.5844 - loss: 0.6613 - val_acc: 0.5060 - val_loss: 0.7246
```

```
Epoch 4/10
32/32            2s 52ms/step - acc:
0.6615 - loss: 0.6468 - val_acc: 0.5048 - val_loss: 0.7486
Epoch 5/10
32/32            3s 51ms/step - acc:
0.7341 - loss: 0.5380 - val_acc: 0.5012 - val_loss: 0.7488
Epoch 6/10
32/32            2s 48ms/step - acc:
0.8366 - loss: 0.4083 - val_acc: 0.5004 - val_loss: 0.9107
Epoch 7/10
32/32            2s 25ms/step - acc:
0.8583 - loss: 0.3908 - val_acc: 0.4956 - val_loss: 2.0459
Epoch 8/10
32/32            1s 26ms/step - acc:
0.8912 - loss: 0.3234 - val_acc: 0.5040 - val_loss: 0.7945
Epoch 9/10
32/32            1s 27ms/step - acc:
0.9778 - loss: 0.1255 - val_acc: 0.4975 - val_loss: 1.0989
Epoch 10/10
32/32            1s 26ms/step - acc:
0.9667 - loss: 0.1447 - val_acc: 0.5087 - val_loss: 1.2214
```





[82]:
```
tst_lss13, tst_a_c_c13 = mdl13.evaluate(XTesting, YTesting)
print('Test loss:', tst_lss13)
print('Test accuracy:', tst_a_c_c13)
```

```
782/782              2s 2ms/step -
acc: 0.4949 - loss: 1.3051
Test loss: 1.2886829376220703
Test accuracy: 0.49911999702453613
```