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| --- | --- | --- |
| Chapter | Status | Notes |
| 1 |  |  |
| 2 |  |  |
| 3 | Initial draft provisionally complete |  |
| 4 | Initial draft provisionally complete | Will be edited to match body of work-Likely after artifact is completed.  Per feedback-rework conclusion  Maybe also intro? |
| 5 | Code Complete  Initial draft provisionally complete |  |
| 6 | Code Complete  Initial draft provisionally complete |  |
| 7 | Idea for architectures identified.  Data collection and cleaning complete over weekend  Basic baseline models Mon/Tues tuned  Work on sentiment attention mechanism between Tues/Wed  Idea for addressing other observations wed/thurs  Implement Thurs/Fri  More optimisation Sat/Sun  Compare to alternative pre-trained models Mon  Write up- happening as the work is being completed |  |
| 8 |  |  |
| 9 |  |  |
| 10 | Write-up up to date with chapter write ups  Need to do section about licenses etc. |  |

#Tokenize the text

ss["text"] = ss["text"].apply(lambda x: word\_tokenize(x))

ss.head()

#Check there are no rows with no tokens- remove if there are

#Count the tokens per row and find rows with zero tokens

zero\_tokens = ss['text'].apply(len) == 0

#Filter to find any rows with no tokens

rows\_with\_zero\_tokens = ss[zero\_tokens]

# Check if there are any rows with zero tokens

if len(rows\_with\_zero\_tokens) > 0:

print("Rows with zero tokens:")

print(rows\_with\_zero\_tokens)

else:

print("No rows with zero tokens found.")

#Drop rows with zero tokens

ss = ss[~zero\_tokens]

ss = ss.reset\_index(drop=True)

#Start at a sequence length and adjust to find the minimum value

target\_sequence\_length = 60

while True:

#Count the tokens per row and find rows with more than the target sequence length

more\_than\_target\_tokens = ss['text'].apply(lambda x: len(x)) > target\_sequence\_length

#Filter to find rows with more than the target sequence length

rows\_with\_more\_than\_target\_tokens = ss[more\_than\_target\_tokens]

#Get the quantity of rows with more than the target sequence length

num\_rows\_with\_more\_than\_target\_tokens = len(rows\_with\_more\_than\_target\_tokens)

#Check if there are any rows with more than the target sequence length

if num\_rows\_with\_more\_than\_target\_tokens > 0:

print(f"Rows with more than {target\_sequence\_length} tokens: {num\_rows\_with\_more\_than\_target\_tokens}")

#Adjust the target sequence length to the maximum length of these rows

target\_sequence\_length = max(rows\_with\_more\_than\_target\_tokens['text'].apply(len))

print(f"Adjusting target sequence length to: {target\_sequence\_length}")

else:

print(f"No rows found with more than {target\_sequence\_length} tokens.")

break

#Now target\_sequence\_length contains the minimum value to have no rows with more tokens than that value

print(f"Minimum sequence length to accommodate all rows: {target\_sequence\_length}")

ss['text'].iloc[0]

#Tokenise text to numeric form for NN

#Create a tokenizer

tokenizer = Tokenizer(num\_words=vocab\_length, oov\_token="<OOV>")

tokenizer.fit\_on\_texts(ss['text'])

#Convert text to sequences of integers

sequences = tokenizer.texts\_to\_sequences(ss['text'])

#Check one example

sequences[0]

#Set the maximum sequence length

max\_sequence\_length = 60

#Iterate through the rows and pad the text data to the max length

for index, sequence in enumerate(sequences):

if len(sequence) < max\_sequence\_length:

#Pad the sequence with zeros at the end

padded\_sequence = sequence + [0] \* (max\_sequence\_length - len(sequence))

else:

#Truncate the sequence if it's longer than the maximum length

padded\_sequence = sequence[:max\_sequence\_length]

#Update the 'text' column with the padded sequence

ss.at[index, 'text'] = padded\_sequence

# Define feature and label columns

X = ss['text']

y = ss['label']

# Split data into test and train

X\_train, X\_test, y\_train, y\_test = train\_test\_split(X, y, test\_size=0.2, random\_state=42)

# Convert training data and labels to numpy arrays

X\_train = np.array(X\_train)

y\_train = np.array(y\_train)

# Check the data shape (optional)

print("X\_train shape:", X\_train.shape)

print("y\_train shape:", y\_train.shape)

# Define the maximum sequence length you want to use

maxlen = 60 # Adjust this value as needed

# Initialize an empty list to store the padded sequences

X\_train\_padded = []

# Iterate through the tokenized sequences and pad each one

for sequence in X\_train:

# Check the length of the sequence

if len(sequence) < maxlen:

# If it's shorter than maxlen, pad it with zeros at the end (not the beginning)

padded\_sequence = sequence + [0] \* (maxlen - len(sequence))

else:

# If it's longer than maxlen, truncate it to maxlen

padded\_sequence = sequence[:maxlen]

# Add the padded sequence to the list

X\_train\_padded.append(padded\_sequence)

# Convert the list of lists to a NumPy array

X\_train\_padded = np.array(X\_train\_padded)

# Now X\_train\_padded is a NumPy array of shape (number\_of\_samples, maxlen)

print("X\_train\_padded shape:", X\_train\_padded.shape)

X\_train\_padded[10]

#Generate vocab from the word tokens

vocab = list(tokenizer.word\_index.keys())

vocab\_length = len(vocab)

#Calculate vocab length

#Create a tokenizer

tokenizer = Tokenizer()

#Fit the tokenizer on your text data

tokenizer.fit\_on\_texts(ss["text"])

#Calculate vocab\_length- add 1 for OOV words

vocab\_length = len(tokenizer.word\_index) + 1

vocab\_length

#Generate vocab from the word tokens

vocab = list(tokenizer.word\_index.keys())

vocab\_length = len(vocab)

#Check this is correct

vocab

#Create numpy array embedding matrix - start empty with a dimensionality of 300 corresponding to the vectors

embedding\_matrix = zeros((vocab\_length, 300))

#For each word in the vocab, check if it is present in the embeddings\_dictionary

for index, word in enumerate(vocab):

if index < vocab\_length:

embedding\_vector = all\_vectors.get(word)

#If it is there, the vector is added to the correct row in the embedding matrix - otherwise, it will just remain zeros

if embedding\_vector is not None:

embedding\_matrix[index] = embedding\_vector

print('Matrix:')

print(embedding\_matrix[1])

print('Vector:')

print(embedding\_vector[1])

#Check shape

embedding\_matrix.shape

#Apply the function to the df with the most words first

vocabulary = build\_vocabulary(df\_a\_emoji)

#Initialize an empty dictionary to store word vectors

word\_vectors = {}

#Iterate through words in your vocabulary

for word in vocabulary:

#Check if the word exists in the Word2Vec model

if word in word2vec\_model:

#Get the word vector

word\_vector = word2vec\_model[word]

#Store the word vector in the dictionary

word\_vectors[word] = word\_vector

#Check for duplicates of rows in df

print(df\_emoji.duplicated(subset=['text'], keep=False).sum())

#Check for null values in dfs

df\_emoji.isnull().sum()

#Set the maximum sequence length

max\_sequence\_length = 60

#Iterate through the rows and pad the text data to the max length

for index, sequence in enumerate(sequences):

if len(sequence) < max\_sequence\_length:

#Pad the sequence with zeros at the end

padded\_sequence = sequence + [0] \* (max\_sequence\_length - len(sequence))

else:

#Truncate the sequence if it's longer than the maximum length

padded\_sequence = sequence[:max\_sequence\_length]

#Update the 'text' column with the padded sequence

ss.at[index, 'text'] = padded\_sequence

# Define feature and label columns

X = ss['text']

y = ss['label']

# Split data into test and train

X\_train, X\_test, y\_train, y\_test = train\_test\_split(X, y, test\_size=0.2, random\_state=42)

# Convert training data and labels to numpy arrays

X\_train = np.array(X\_train)

y\_train = np.array(y\_train)

# Check the data shape (optional)

print("X\_train shape:", X\_train.shape)

print("y\_train shape:", y\_train.shape)

X\_train[0]

# Define the maximum sequence length you want to use

maxlen = 60 # Adjust this value as needed

# Initialize an empty list to store the padded sequences

X\_train\_padded = []

# Iterate through the tokenized sequences and pad each one

for sequence in X\_train:

# Check the length of the sequence

if len(sequence) < maxlen:

# If it's shorter than maxlen, pad it with zeros at the end (not the beginning)

padded\_sequence = sequence + [0] \* (maxlen - len(sequence))

else:

# If it's longer than maxlen, truncate it to maxlen

padded\_sequence = sequence[:maxlen]

# Add the padded sequence to the list

X\_train\_padded.append(padded\_sequence)

# Convert the list of lists to a NumPy array

X\_train\_padded = np.array(X\_train\_padded)

# Now X\_train\_padded is a NumPy array of shape (number\_of\_samples, maxlen)

print("X\_train\_padded shape:", X\_train\_padded.shape)

X\_train\_padded[10]

#Make sure this is converting back to words in a way that makes sense

#Sequence of integers

sequence = X\_test\_padded[0]

#Convert sequence back to words

decoded\_words = [tokenizer.index\_word.get(idx, "<OOV>") for idx in sequence]

#Join the words to form the original text

original\_text = " ".join(decoded\_words)

#Check if this makes sense

print(original\_text)