0.1 Implement the Continuous Bag of Words (CBOW) Model. Stages can be:

a. Data preparation
b. Generate training data
c. Train model
d. Output

[2]:
```
import numpy as np
import re
```

[3]:
```
data = """Deep learning (also known as deep structured learning) is part of a␣
↪broader family of machine learning methods based on artificial neural␣
↪networks with representation learning. Learning can be supervised,␣
↪semi-supervised or unsupervised. Deep-learning architectures such as deep␣
↪neural networks, deep belief networks, deep reinforcement learning,␣
↪recurrent neural networks, convolutional neural networks and Transformers␣
↪have been applied to fields including computer vision, speech recognition,␣
↪natural language processing, machine translation, bioinformatics, drug␣
↪design, medical image analysis, climate science, material inspection and␣
↪board game programs, where they have produced results comparable to and in␣
↪some cases surpassing human expert performance."""
data
```

[3]:
```
'Deep learning (also known as deep structured learning) is part of a broader
family of machine learning methods based on artificial neural networks with
representation learning. Learning can be supervised, semi-supervised or
unsupervised. Deep-learning architectures such as deep neural networks, deep
belief networks, deep reinforcement learning, recurrent neural networks,
convolutional neural networks and Transformers have been applied to fields
including computer vision, speech recognition, natural language processing,
machine translation, bioinformatics, drug design, medical image analysis,
climate science, material inspection and board game programs, where they have
produced results comparable to and in some cases surpassing human expert
performance.'
```

[4]:
```
sentences = data.split('.')
sentences
```

[4]:

```
['Deep learning (also known as deep structured learning) is part of a broader
family of machine learning methods based on artificial neural networks with
representation learning',
 ' Learning can be supervised, semi-supervised or unsupervised',
 ' Deep-learning architectures such as deep neural networks, deep belief
networks, deep reinforcement learning, recurrent neural networks, convolutional
neural networks and Transformers have been applied to fields including computer
vision, speech recognition, natural language processing, machine translation,
bioinformatics, drug design, medical image analysis, climate science, material
inspection and board game programs, where they have produced results comparable
to and in some cases surpassing human expert performance',
 '']
```

[6]:

```python
clean_sent=[]
for sentence in sentences:
    if sentence=="":
        continue
    sentence = re.sub('[^A-Za-z0-9]+', ' ', (sentence))
    sentence = re.sub(r'(?:^| )\w (?:$| )', ' ', (sentence)).strip()
    sentence = sentence.lower()
    clean_sent.append(sentence)

print(clean_sent)
```

```
['deep learning also known as deep structured learning is part of a broader
family of machine learning methods based on artificial neural networks with
representation learning', 'learning can be supervised semi supervised or
unsupervised', 'deep learning architectures such as deep neural networks deep
belief networks deep reinforcement learning recurrent neural networks
convolutional neural networks and transformers have been applied to fields
including computer vision speech recognition natural language processing machine
translation bioinformatics drug design medical image analysis climate science
material inspection and board game programs where they have produced results
comparable to and in some cases surpassing human expert performance']
```

[7]:

```python
from tensorflow.keras.preprocessing.text import Tokenizer
#The Tokenizer is a utility that helps in converting text into a format␣
↪suitable for
#machine learning models. It will convert words into integer indices, which can␣
↪then be used for training.
```

[11]:

```python
tokenizer = Tokenizer()
tokenizer.fit_on_texts(clean_sent)
sequences = tokenizer.texts_to_sequences(clean_sent)
print(sequences)
```

```
[[2, 1, 12, 13, 6, 2, 14, 1, 15, 16, 7, 17, 18, 19, 7, 8, 1, 20, 21, 22, 23, 4,
3, 24, 25, 1], [1, 26, 27, 9, 28, 9, 29, 30], [2, 1, 31, 32, 6, 2, 4, 3, 2, 33,
```

```
3, 2, 34, 1, 35, 4, 3, 36, 4, 3, 5, 37, 10, 38, 39, 11, 40, 41, 42, 43, 44, 45,
46, 47, 48, 8, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 5, 60, 61, 62, 63,
64, 10, 65, 66, 67, 11, 5, 68, 69, 70, 71, 72, 73, 74]]
```

[15]:
```python
index_to_word = {}
word_to_index = {}

for i, sequence in enumerate(sequences):
#     print(sequence)
    word_in_sentence = clean_sent[i].split()
#     print(word_in_sentence)

    for j, value in enumerate(sequence):
        index_to_word[value] = word_in_sentence[j]
        word_to_index[word_in_sentence[j]] = value

print(index_to_word, "\n")
print(word_to_index)
```

```
{2: 'deep', 1: 'learning', 12: 'also', 13: 'known', 6: 'as', 14: 'structured',
15: 'is', 16: 'part', 7: 'of', 17: 'a', 18: 'broader', 19: 'family', 8:
'machine', 20: 'methods', 21: 'based', 22: 'on', 23: 'artificial', 4: 'neural',
3: 'networks', 24: 'with', 25: 'representation', 26: 'can', 27: 'be', 9:
'supervised', 28: 'semi', 29: 'or', 30: 'unsupervised', 31: 'architectures', 32:
'such', 33: 'belief', 34: 'reinforcement', 35: 'recurrent', 36: 'convolutional',
5: 'and', 37: 'transformers', 10: 'have', 38: 'been', 39: 'applied', 11: 'to',
40: 'fields', 41: 'including', 42: 'computer', 43: 'vision', 44: 'speech', 45:
'recognition', 46: 'natural', 47: 'language', 48: 'processing', 49:
'translation', 50: 'bioinformatics', 51: 'drug', 52: 'design', 53: 'medical',
54: 'image', 55: 'analysis', 56: 'climate', 57: 'science', 58: 'material', 59:
'inspection', 60: 'board', 61: 'game', 62: 'programs', 63: 'where', 64: 'they',
65: 'produced', 66: 'results', 67: 'comparable', 68: 'in', 69: 'some', 70:
'cases', 71: 'surpassing', 72: 'human', 73: 'expert', 74: 'performance'}

{'deep': 2, 'learning': 1, 'also': 12, 'known': 13, 'as': 6, 'structured': 14,
'is': 15, 'part': 16, 'of': 7, 'a': 17, 'broader': 18, 'family': 19, 'machine':
8, 'methods': 20, 'based': 21, 'on': 22, 'artificial': 23, 'neural': 4,
'networks': 3, 'with': 24, 'representation': 25, 'can': 26, 'be': 27,
'supervised': 9, 'semi': 28, 'or': 29, 'unsupervised': 30, 'architectures': 31,
'such': 32, 'belief': 33, 'reinforcement': 34, 'recurrent': 35, 'convolutional':
36, 'and': 5, 'transformers': 37, 'have': 10, 'been': 38, 'applied': 39, 'to':
11, 'fields': 40, 'including': 41, 'computer': 42, 'vision': 43, 'speech': 44,
'recognition': 45, 'natural': 46, 'language': 47, 'processing': 48,
'translation': 49, 'bioinformatics': 50, 'drug': 51, 'design': 52, 'medical':
53, 'image': 54, 'analysis': 55, 'climate': 56, 'science': 57, 'material': 58,
'inspection': 59, 'board': 60, 'game': 61, 'programs': 62, 'where': 63, 'they':
64, 'produced': 65, 'results': 66, 'comparable': 67, 'in': 68, 'some': 69,
'cases': 70, 'surpassing': 71, 'human': 72, 'expert': 73, 'performance': 74}
```

[44]:
```
#this code segment prepares the context and target data for the Continuous Bag␣
↪of Words (CBOW) model

vocab_size = len(tokenizer.word_index) + 1
#This line calculates the vocabulary size, which is the number of unique words␣
↪in your dataset. tokenizer.word_index returns a dictionary of words mapped␣
↪to their corresponding indices.
#The +1 accounts for the fact that indexing starts at 1 (as 0 is often reserved␣
↪for padding in neural networks)
emb_size = 10
# emb_size is set to 10. This variable defines the size of the embedding␣
↪vectors that will be used to represent each word.
# An embedding size of 10 means each word will be represented by a vector of 10␣
↪numbers.
context_size = 2

contexts = []
targets = []

for sequence in sequences:

    for i in range(context_size, len(sequence) - context_size):
      #This inner loop iterates through the indices of the current sequence,␣
↪starting from context_size and ending at len(sequence) - context_size.
      #This ensures that the model has enough words on both sides of the target␣
↪word to create a full context window.

        target = sequence[i]

        context = [sequence[i - 2], sequence[i - 1], sequence[i + 1],␣
↪sequence[i + 2]]
#         print(context)
        contexts.append(context)
        targets.append(target)
print('context --> ',contexts, "\n")
print('targets --> ', targets)
```

```
context -->  [[2, 1, 13, 6], [1, 12, 6, 2], [12, 13, 2, 14], [13, 6, 14, 1], [6,
2, 1, 15], [2, 14, 15, 16], [14, 1, 16, 7], [1, 15, 7, 17], [15, 16, 17, 18],
[16, 7, 18, 19], [7, 17, 19, 7], [17, 18, 7, 8], [18, 19, 8, 1], [19, 7, 1, 20],
[7, 8, 20, 21], [8, 1, 21, 22], [1, 20, 22, 23], [20, 21, 23, 4], [21, 22, 4,
3], [22, 23, 3, 24], [23, 4, 24, 25], [4, 3, 25, 1], [1, 26, 9, 28], [26, 27,
28, 9], [27, 9, 9, 29], [9, 28, 29, 30], [2, 1, 32, 6], [1, 31, 6, 2], [31, 32,
2, 4], [32, 6, 4, 3], [6, 2, 3, 2], [2, 4, 2, 33], [4, 3, 33, 3], [3, 2, 3, 2],
[2, 33, 2, 34], [33, 3, 34, 1], [3, 2, 1, 35], [2, 34, 35, 4], [34, 1, 4, 3],
[1, 35, 3, 36], [35, 4, 36, 4], [4, 3, 4, 3], [3, 36, 3, 5], [36, 4, 5, 37], [4,
3, 37, 10], [3, 5, 10, 38], [5, 37, 38, 39], [37, 10, 39, 11], [10, 38, 11, 40],
```

```
[38, 39, 40, 41], [39, 11, 41, 42], [11, 40, 42, 43], [40, 41, 43, 44], [41, 42,
44, 45], [42, 43, 45, 46], [43, 44, 46, 47], [44, 45, 47, 48], [45, 46, 48, 8],
[46, 47, 8, 49], [47, 48, 49, 50], [48, 8, 50, 51], [8, 49, 51, 52], [49, 50,
52, 53], [50, 51, 53, 54], [51, 52, 54, 55], [52, 53, 55, 56], [53, 54, 56, 57],
[54, 55, 57, 58], [55, 56, 58, 59], [56, 57, 59, 5], [57, 58, 5, 60], [58, 59,
60, 61], [59, 5, 61, 62], [5, 60, 62, 63], [60, 61, 63, 64], [61, 62, 64, 10],
[62, 63, 10, 65], [63, 64, 65, 66], [64, 10, 66, 67], [10, 65, 67, 11], [65, 66,
11, 5], [66, 67, 5, 68], [67, 11, 68, 69], [11, 5, 69, 70], [5, 68, 70, 71],
[68, 69, 71, 72], [69, 70, 72, 73], [70, 71, 73, 74]]

targets -->  [12, 13, 6, 2, 14, 1, 15, 16, 7, 17, 18, 19, 7, 8, 1, 20, 21, 22,
23, 4, 3, 24, 27, 9, 28, 9, 31, 32, 6, 2, 4, 3, 2, 33, 3, 2, 34, 1, 35, 4, 3,
36, 4, 3, 5, 37, 10, 38, 39, 11, 40, 41, 42, 43, 44, 45, 46, 47, 48, 8, 49, 50,
51, 52, 53, 54, 55, 56, 57, 58, 59, 5, 60, 61, 62, 63, 64, 10, 65, 66, 67, 11,
5, 68, 69, 70, 71, 72]
```

[41]:
```python
#printing features with target
for i in range(5):
    words = []
    target = index_to_word.get(targets[i])
    for j in contexts[i]:
        words.append(index_to_word.get(j))
    print(words," --> ", target, '\n')
```

```
['deep', 'learning', 'known', 'as']  -->  also

['learning', 'also', 'as', 'deep']  -->  known

['also', 'known', 'deep', 'structured']  -->  as

['known', 'as', 'structured', 'learning']  -->  deep

['as', 'deep', 'learning', 'is']  -->  structured
```

[37]:
```python
# Convert the contexts and targets to numpy arrays
X = np.array(contexts)
Y = np.array(targets)
X.shape, Y.shape
```

[37]: ((88, 4), (88,))

[42]:
```python
# print(X)
# print(Y)
```

[45]:
```python
import tensorflow as tf
from tensorflow.keras.models import Sequential
```

```
from tensorflow.keras.layers import Dense, Embedding, Lambda

# Sequential: This class is used to create a linear stack of layers for the␣
↪model.
# Dense: A fully connected layer used for the model.
# Embedding: A layer that turns positive integers (indexes) into dense vectors␣
↪of fixed size.
# Lambda: A layer that allows you to create custom operations in your model.
```

[66]:
```
# This initializes a sequential model, which is built layer by layer.
model = Sequential([

# This layer transforms the integer indices from the contexts into dense␣
↪vectors (embeddings).
# input_dim=vocab_size: The size of the input space (number of unique words).
# output_dim=emb_size: The size of the embedding vectors (10 in this case).
# input_length=2*context_size: The length of the input sequences (4 in this␣
↪case, as context_size is set to 2).
    Embedding(input_dim=vocab_size, output_dim=emb_size,␣
↪input_length=2*context_size),

# This layer computes the mean of the embedding vectors for each context (which␣
↪contains 4 words).
# tf.reduce_mean(x, axis=1) calculates the average across the embedding vectors␣
↪along the specified axis (in this case, the context dimension).
# The output will be a single vector for each input context, summarizing the␣
↪information from the four context words.
    Lambda(lambda x: tf.reduce_mean(x, axis=1)),

#This fully connected layer has 256 units and uses the ReLU (Rectified Linear␣
↪Unit) activation function.
#It introduces non-linearity to the model, allowing it to learn complex␣
↪relationships.
    Dense(256, activation='relu'),
    Dense(512, activation='relu'),

# The output layer has a number of units equal to the vocabulary size and uses␣
↪the softmax activation function.
# The softmax function outputs a probability distribution over the vocabulary,␣
↪predicting the likelihood of each word being the target given the context.
    Dense(vocab_size, activation='softmax')
])
```

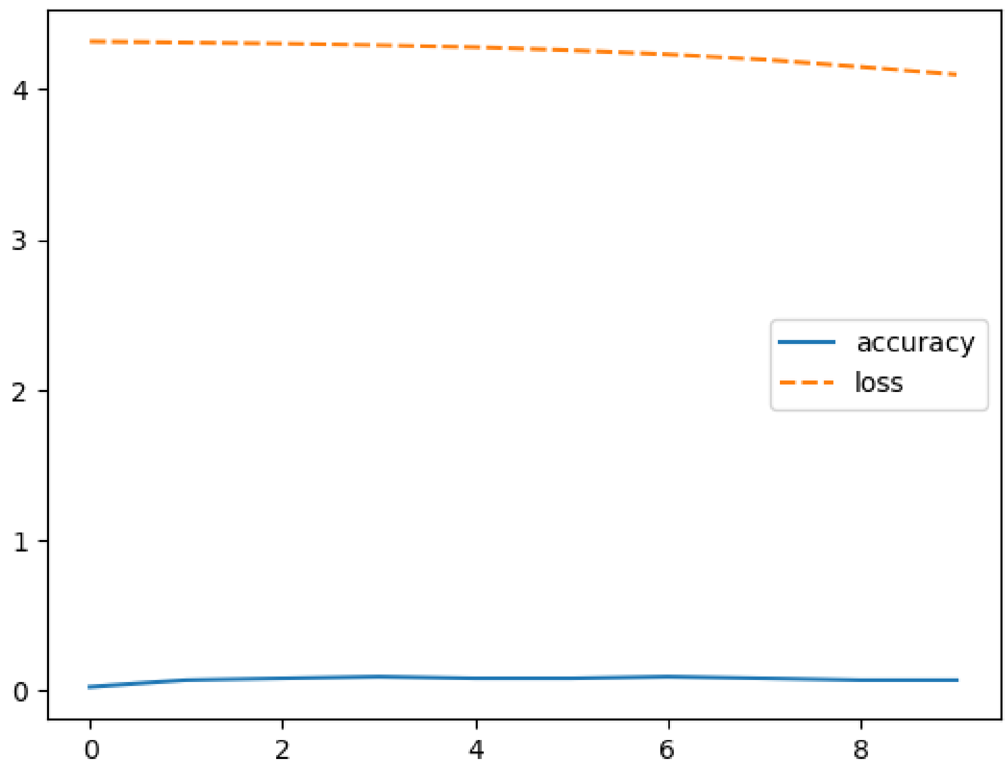
[67]:
```
model.compile(loss='sparse_categorical_crossentropy', optimizer='adam',␣
↪metrics=['accuracy'])
```

[70]:
```python
history=model.fit(X, Y, epochs=10)
# This line trains the model on the training data (X for contexts and Y for␣
↪targets) for 80 epochs.
# During each epoch, the model will go through all the training data, updating␣
↪its weights to minimize the loss function.
# The fit method returns a history object that contains information about the␣
↪training process, including loss and accuracy for each epoch.
```

```
Epoch 1/10
3/3              0s 8ms/step -
accuracy: 0.0732 - loss: 4.0512
Epoch 2/10
3/3              0s 8ms/step -
accuracy: 0.0597 - loss: 3.9213
Epoch 3/10
3/3              0s 7ms/step -
accuracy: 0.0597 - loss: 3.8948
Epoch 4/10
3/3              0s 7ms/step -
accuracy: 0.0518 - loss: 3.8924
Epoch 5/10
3/3              0s 7ms/step -
accuracy: 0.0810 - loss: 3.8144
Epoch 6/10
3/3              0s 10ms/step -
accuracy: 0.0692 - loss: 3.7104
Epoch 7/10
3/3              0s 10ms/step -
accuracy: 0.1037 - loss: 3.6339
Epoch 8/10
3/3              0s 10ms/step -
accuracy: 0.1712 - loss: 3.5444
Epoch 9/10
3/3              0s 8ms/step -
accuracy: 0.1942 - loss: 3.4525
Epoch 10/10
3/3              0s 8ms/step -
accuracy: 0.2035 - loss: 3.4958
```

[69]:
```python
import seaborn as sns
sns.lineplot(model.history.history)
```

[69]: <Axes: >



[63]:
```
# test model: select some sentences from above paragraph
test_sentenses = [
    "known as structured learning",
    "transformers have applied to",
    "where they produced results",
    "cases surpassing expert performance"
]
```

[64]:
```
for sent in test_sentenses:
    test_words = sent.split(" ")
#     print(test_words)
    x_test =[]
    for i in test_words:
        x_test.append(word_to_index.get(i))
    x_test = np.array([x_test])
#     print(x_test)

    pred = model.predict(x_test)
    pred = np.argmax(pred[0])
    print("pred ", test_words, "\n=", index_to_word.get(pred),"\n\n")
```

```
1/1              0s 19ms/step
```

```
pred  ['known', 'as', 'structured', 'learning']
= deep


1/1             0s 19ms/step
pred  ['transformers', 'have', 'applied', 'to']
= been


1/1             0s 18ms/step
pred  ['where', 'they', 'produced', 'results']
= have


1/1             0s 22ms/step
pred  ['cases', 'surpassing', 'expert', 'performance']
= human
```