

1. Implement the Continuous Bag of Words (CBOW) Model. Stages can be:
 - a. Data preparation
 - b. Generate training data
 - c. Train model
 - d. Output

```
In [1]: import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, \
    Embedding, Lambda
from tensorflow.keras.preprocessing.text import Tokenizer
import numpy as np
import matplotlib.pyplot as plt
from sklearn.decomposition import PCA
import re
```

2023-11-05 10:46:30.013620: I tensorflow/core/platform/cpu_feature_guard.cc:182] This TensorFlow binary is optimized to use available CPU instructions in performance-critical operations.
To enable the following instructions: AVX2 FMA, in other operations, rebuild TensorFlow with the appropriate compiler flags.

a. Data preparation

```
In [2]: data = """We are about to study the idea of a computational process.
Computational processes are abstract beings that inhabit computers.
As they evolve, processes manipulate other abstract things called data.
The evolution of a process is directed by a pattern of rules
called a program. People create programs to direct processes. In effect,
we conjure the spirits of the computer with our spells."""
```

```
In [3]: # for importing data from txt file
# with open("data.txt", "r", encoding="utf-8") as file:
#     data = file.read()
```

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

```
In [5]: sentences
```

```
Out[5]: ['We are about to study the idea of a computational process',
'\nComputational processes are abstract beings that inhabit computers',
'\nAs they evolve, processes manipulate other abstract things called data',
'\nThe evolution of a process is directed by a pattern of rules\ncalled a program',
' People create programs to direct processes',
' In effect,\nwe conjure the spirits of the computer with our spells',
'']
```

```
In [6]: #Clean Data
clean_sentences = []
for sentence in sentences:
    # skip empty string
```

```

if sentence == "":
    continue;
# remove special characters
sentence = re.sub('[^A-Za-z0-9]+', ' ', sentence)
# remove 1 letter words
sentence = re.sub(r'(?<^| )\w(?:$| )', ' ', sentence).strip()
# lower all characters
sentence = sentence.lower()
clean_sentences.append(sentence)

```

In [7]: clean_sentences

```

Out[7]: ['we are about to study the idea of computational process',
'computational processes are abstract beings that inhabit computers',
'as they evolve processes manipulate other abstract things called data',
'the evolution of process is directed by pattern of rules called program',
'people create programs to direct processes',
'in effect we conjure the spirits of the computer with our spells']

```

In [8]: *# Define the corpus*
corpus = clean_sentences

In [9]: *# Convert the corpus to a sequence of integers*
tokenizer = Tokenizer()
tokenizer.fit_on_texts(corpus)
sequences = tokenizer.texts_to_sequences(corpus)
print("After converting our words in the corpus \\
into vector of integers:")
print(sequences)

After converting our words in the corpus into vector of integers:
[[4, 5, 11, 6, 12, 1, 13, 2, 7, 8], [7, 3, 5, 9, 14, 15, 16, 17], [18, 19, 20, 3, 21, 22, 9, 23, 10, 24], [1, 25, 2, 8, 26, 27, 28, 29, 2, 30, 10, 31], [32, 33, 34, 6, 35, 3], [36, 37, 4, 38, 1, 39, 2, 1, 40, 41, 42, 43]]

In [10]: *# creating dictionary for word to index and index to word*
index_to_word_map = {}
word_to_index_map = {}
for index_1, sequence in enumerate(sequences):
 print(sequence)
 words_in_sentence = clean_sentences[index_1].split()
 print(words_in_sentence)
 for index_2, value in enumerate(sequence):
 index_to_word_map[value] = words_in_sentence[index_2]
 word_to_index_map[words_in_sentence[index_2]] = value

```

[4, 5, 11, 6, 12, 1, 13, 2, 7, 8]
['we', 'are', 'about', 'to', 'study', 'the', 'idea', 'of', 'computational', 'process']
[7, 3, 5, 9, 14, 15, 16, 17]
['computational', 'processes', 'are', 'abstract', 'beings', 'that', 'inhabit', 'computers']
[18, 19, 20, 3, 21, 22, 9, 23, 10, 24]
['as', 'they', 'evolve', 'processes', 'manipulate', 'other', 'abstract', 'things', 'called', 'data']
[1, 25, 2, 8, 26, 27, 28, 29, 2, 30, 10, 31]
['the', 'evolution', 'of', 'process', 'is', 'directed', 'by', 'pattern', 'of', 'rules', 'called', 'program']
[32, 33, 34, 6, 35, 3]
['people', 'create', 'programs', 'to', 'direct', 'processes']
[36, 37, 4, 38, 1, 39, 2, 1, 40, 41, 42, 43]
['in', 'effect', 'we', 'conjure', 'the', 'spirits', 'of', 'the', 'computer', 'with', 'our', 'spells']

```

```

In [11]: print(index_to_word_map)
print("\n")
print(word_to_index_map)

```

```

{4: 'we', 5: 'are', 11: 'about', 6: 'to', 12: 'study', 1: 'the', 13: 'idea', 2: 'of', 7: 'computational', 8: 'process', 3: 'processes', 9: 'abstract', 14: 'beings', 15: 'that', 16: 'inhabit', 17: 'computers', 18: 'as', 19: 'they', 20: 'evolve', 21: 'manipulate', 22: 'other', 23: 'things', 10: 'called', 24: 'data', 25: 'evolution', 26: 'is', 27: 'directed', 28: 'by', 29: 'pattern', 30: 'rules', 31: 'program', 32: 'people', 33: 'create', 34: 'programs', 35: 'direct', 36: 'in', 37: 'effect', 38: 'conjure', 39: 'spirits', 40: 'computer', 41: 'with', 42: 'our', 43: 'spells'}

```

```

{'we': 4, 'are': 5, 'about': 11, 'to': 6, 'study': 12, 'the': 1, 'idea': 13, 'of': 2, 'computational': 7, 'process': 8, 'processes': 3, 'abstract': 9, 'beings': 14, 'that': 15, 'inhabit': 16, 'computers': 17, 'as': 18, 'they': 19, 'evolve': 20, 'manipulate': 21, 'other': 22, 'things': 23, 'called': 10, 'data': 24, 'evolution': 25, 'is': 26, 'directed': 27, 'by': 28, 'pattern': 29, 'rules': 30, 'program': 31, 'people': 32, 'create': 33, 'programs': 34, 'direct': 35, 'in': 36, 'effect': 37, 'conjure': 38, 'spirits': 39, 'computer': 40, 'with': 41, 'our': 42, 'spells': 43}

```

b. Generate training data

```

In [12]: # Define the parameters
vocab_size = len(tokenizer.word_index) + 1
embedding_size = 10
window_size = 2

# Generate the context-target pairs
contexts = []
targets = []
for sequence in sequences:
    for i in range(window_size, len(sequence) - window_size):
        context = sequence[i - window_size:i] + sequence[i + 1:i + window_size]
        target = sequence[i]
        contexts.append(context)
        targets.append(target)

```

```
In [13]: # sample of training data
for i in range(5):
    words = []
    target = index_to_word_map.get(targets[i])
    for j in contexts[i]:
        words.append(index_to_word_map.get(j))
    print(words, "=>", target)
```

```
['we', 'are', 'to', 'study'] => about
['are', 'about', 'study', 'the'] => to
['about', 'to', 'the', 'idea'] => study
['to', 'study', 'idea', 'of'] => the
['study', 'the', 'of', 'computational'] => idea
```

```
In [14]: # Convert the contexts and targets to numpy arrays
X = np.array(contexts)
Y = np.array(targets)
```

c. Train model

```
In [15]: # Define the CBOW model
model = Sequential()
model.add(Embedding(input_dim=vocab_size, output_dim=embedding_size, input_length=contexts_max_length))
model.add(Lambda(lambda x: tf.reduce_mean(x, axis=1)))
model.add(Dense(256, activation='relu'))
model.add(Dense(512, activation='relu'))
model.add(Dense(units=vocab_size, activation='softmax'))

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

# Train the model
model.fit(X, Y, epochs=200, verbose=1)
```

Epoch 1/200
2/2 [=====] - 0s 8ms/step - loss: 3.7840 - accuracy: 0.0294
Epoch 2/200
2/2 [=====] - 0s 6ms/step - loss: 3.7747 - accuracy: 0.1765
Epoch 3/200
2/2 [=====] - 0s 6ms/step - loss: 3.7670 - accuracy: 0.1176
Epoch 4/200
2/2 [=====] - 0s 7ms/step - loss: 3.7590 - accuracy: 0.1176
Epoch 5/200
2/2 [=====] - 0s 6ms/step - loss: 3.7490 - accuracy: 0.1176
Epoch 6/200
2/2 [=====] - 0s 6ms/step - loss: 3.7379 - accuracy: 0.1176
Epoch 7/200
2/2 [=====] - 0s 7ms/step - loss: 3.7251 - accuracy: 0.1176
Epoch 8/200
2/2 [=====] - 0s 6ms/step - loss: 3.7099 - accuracy: 0.1176
Epoch 9/200
2/2 [=====] - 0s 7ms/step - loss: 3.6919 - accuracy: 0.1176
Epoch 10/200
2/2 [=====] - 0s 5ms/step - loss: 3.6711 - accuracy: 0.1471
Epoch 11/200
2/2 [=====] - 0s 6ms/step - loss: 3.6471 - accuracy: 0.1471
Epoch 12/200
2/2 [=====] - 0s 5ms/step - loss: 3.6184 - accuracy: 0.1176
Epoch 13/200
2/2 [=====] - 0s 6ms/step - loss: 3.5851 - accuracy: 0.1176
Epoch 14/200
2/2 [=====] - 0s 5ms/step - loss: 3.5477 - accuracy: 0.1176
Epoch 15/200
2/2 [=====] - 0s 5ms/step - loss: 3.5061 - accuracy: 0.1176
Epoch 16/200
2/2 [=====] - 0s 6ms/step - loss: 3.4633 - accuracy: 0.1176
Epoch 17/200
2/2 [=====] - 0s 8ms/step - loss: 3.4173 - accuracy: 0.1176
Epoch 18/200
2/2 [=====] - 0s 6ms/step - loss: 3.3707 - accuracy: 0.1176
Epoch 19/200
2/2 [=====] - 0s 5ms/step - loss: 3.3228 - accuracy: 0.1176
Epoch 20/200
2/2 [=====] - 0s 5ms/step - loss: 3.2718 - accuracy:

cy: 0.1176
Epoch 21/200
2/2 [=====] - 0s 6ms/step - loss: 3.2240 - accuracy: 0.1176
Epoch 22/200
2/2 [=====] - 0s 5ms/step - loss: 3.1789 - accuracy: 0.1176
Epoch 23/200
2/2 [=====] - 0s 5ms/step - loss: 3.1368 - accuracy: 0.1471
Epoch 24/200
2/2 [=====] - 0s 4ms/step - loss: 3.1041 - accuracy: 0.1471
Epoch 25/200
2/2 [=====] - 0s 5ms/step - loss: 3.0692 - accuracy: 0.1471
Epoch 26/200
2/2 [=====] - 0s 5ms/step - loss: 3.0417 - accuracy: 0.1471
Epoch 27/200
2/2 [=====] - 0s 6ms/step - loss: 3.0187 - accuracy: 0.1471
Epoch 28/200
2/2 [=====] - 0s 5ms/step - loss: 3.0006 - accuracy: 0.1176
Epoch 29/200
2/2 [=====] - 0s 6ms/step - loss: 2.9701 - accuracy: 0.1176
Epoch 30/200
2/2 [=====] - 0s 5ms/step - loss: 2.9323 - accuracy: 0.1176
Epoch 31/200
2/2 [=====] - 0s 5ms/step - loss: 2.8934 - accuracy: 0.1176
Epoch 32/200
2/2 [=====] - 0s 5ms/step - loss: 2.8603 - accuracy: 0.1471
Epoch 33/200
2/2 [=====] - 0s 6ms/step - loss: 2.8345 - accuracy: 0.1765
Epoch 34/200
2/2 [=====] - 0s 5ms/step - loss: 2.8075 - accuracy: 0.2353
Epoch 35/200
2/2 [=====] - 0s 5ms/step - loss: 2.7839 - accuracy: 0.2647
Epoch 36/200
2/2 [=====] - 0s 6ms/step - loss: 2.7592 - accuracy: 0.2647
Epoch 37/200
2/2 [=====] - 0s 5ms/step - loss: 2.7336 - accuracy: 0.2647
Epoch 38/200
2/2 [=====] - 0s 5ms/step - loss: 2.7042 - accuracy: 0.2353
Epoch 39/200
2/2 [=====] - 0s 6ms/step - loss: 2.6726 - accuracy: 0.2353
Epoch 40/200

2/2 [=====] - 0s 5ms/step - loss: 2.6350 - accuracy: 0.2647
Epoch 41/200
2/2 [=====] - 0s 5ms/step - loss: 2.5918 - accuracy: 0.2353
Epoch 42/200
2/2 [=====] - 0s 6ms/step - loss: 2.5551 - accuracy: 0.2647
Epoch 43/200
2/2 [=====] - 0s 5ms/step - loss: 2.5199 - accuracy: 0.2647
Epoch 44/200
2/2 [=====] - 0s 5ms/step - loss: 2.4888 - accuracy: 0.2353
Epoch 45/200
2/2 [=====] - 0s 5ms/step - loss: 2.4622 - accuracy: 0.2353
Epoch 46/200
2/2 [=====] - 0s 5ms/step - loss: 2.4347 - accuracy: 0.2647
Epoch 47/200
2/2 [=====] - 0s 5ms/step - loss: 2.4077 - accuracy: 0.2941
Epoch 48/200
2/2 [=====] - 0s 4ms/step - loss: 2.3822 - accuracy: 0.3235
Epoch 49/200
2/2 [=====] - 0s 5ms/step - loss: 2.3580 - accuracy: 0.3235
Epoch 50/200
2/2 [=====] - 0s 5ms/step - loss: 2.3299 - accuracy: 0.2941
Epoch 51/200
2/2 [=====] - 0s 6ms/step - loss: 2.3047 - accuracy: 0.3235
Epoch 52/200
2/2 [=====] - 0s 5ms/step - loss: 2.2747 - accuracy: 0.3235
Epoch 53/200
2/2 [=====] - 0s 5ms/step - loss: 2.2469 - accuracy: 0.3235
Epoch 54/200
2/2 [=====] - 0s 5ms/step - loss: 2.2179 - accuracy: 0.3235
Epoch 55/200
2/2 [=====] - 0s 4ms/step - loss: 2.1988 - accuracy: 0.3529
Epoch 56/200
2/2 [=====] - 0s 4ms/step - loss: 2.1861 - accuracy: 0.3824
Epoch 57/200
2/2 [=====] - 0s 5ms/step - loss: 2.1612 - accuracy: 0.3824
Epoch 58/200
2/2 [=====] - 0s 5ms/step - loss: 2.1344 - accuracy: 0.3824
Epoch 59/200
2/2 [=====] - 0s 6ms/step - loss: 2.0989 - accuracy: 0.3824

Epoch 60/200
2/2 [=====] - 0s 6ms/step - loss: 2.0641 - accuracy: 0.3824
Epoch 61/200
2/2 [=====] - 0s 6ms/step - loss: 2.0409 - accuracy: 0.3824
Epoch 62/200
2/2 [=====] - 0s 4ms/step - loss: 2.0243 - accuracy: 0.4118
Epoch 63/200
2/2 [=====] - 0s 5ms/step - loss: 2.0030 - accuracy: 0.4118
Epoch 64/200
2/2 [=====] - 0s 5ms/step - loss: 1.9711 - accuracy: 0.4118
Epoch 65/200
2/2 [=====] - 0s 5ms/step - loss: 1.9392 - accuracy: 0.4118
Epoch 66/200
2/2 [=====] - 0s 6ms/step - loss: 1.9070 - accuracy: 0.4412
Epoch 67/200
2/2 [=====] - 0s 5ms/step - loss: 1.8823 - accuracy: 0.4412
Epoch 68/200
2/2 [=====] - 0s 4ms/step - loss: 1.8635 - accuracy: 0.4118
Epoch 69/200
2/2 [=====] - 0s 5ms/step - loss: 1.8362 - accuracy: 0.4118
Epoch 70/200
2/2 [=====] - 0s 4ms/step - loss: 1.8038 - accuracy: 0.5000
Epoch 71/200
2/2 [=====] - 0s 4ms/step - loss: 1.7620 - accuracy: 0.5000
Epoch 72/200
2/2 [=====] - 0s 4ms/step - loss: 1.7261 - accuracy: 0.4412
Epoch 73/200
2/2 [=====] - 0s 5ms/step - loss: 1.6860 - accuracy: 0.5000
Epoch 74/200
2/2 [=====] - 0s 4ms/step - loss: 1.6592 - accuracy: 0.5000
Epoch 75/200
2/2 [=====] - 0s 4ms/step - loss: 1.6409 - accuracy: 0.5294
Epoch 76/200
2/2 [=====] - 0s 4ms/step - loss: 1.6168 - accuracy: 0.5000
Epoch 77/200
2/2 [=====] - 0s 4ms/step - loss: 1.5851 - accuracy: 0.4706
Epoch 78/200
2/2 [=====] - 0s 5ms/step - loss: 1.5540 - accuracy: 0.5294
Epoch 79/200
2/2 [=====] - 0s 4ms/step - loss: 1.5164 - accuracy:

cy: 0.5294
Epoch 80/200
2/2 [=====] - 0s 4ms/step - loss: 1.4713 - accuracy: 0.5588
Epoch 81/200
2/2 [=====] - 0s 4ms/step - loss: 1.4381 - accuracy: 0.5588
Epoch 82/200
2/2 [=====] - 0s 5ms/step - loss: 1.4111 - accuracy: 0.5588
Epoch 83/200
2/2 [=====] - 0s 5ms/step - loss: 1.3882 - accuracy: 0.6471
Epoch 84/200
2/2 [=====] - 0s 4ms/step - loss: 1.3698 - accuracy: 0.6471
Epoch 85/200
2/2 [=====] - 0s 4ms/step - loss: 1.3491 - accuracy: 0.6471
Epoch 86/200
2/2 [=====] - 0s 4ms/step - loss: 1.3175 - accuracy: 0.6765
Epoch 87/200
2/2 [=====] - 0s 4ms/step - loss: 1.2793 - accuracy: 0.6471
Epoch 88/200
2/2 [=====] - 0s 4ms/step - loss: 1.2423 - accuracy: 0.6176
Epoch 89/200
2/2 [=====] - 0s 5ms/step - loss: 1.2128 - accuracy: 0.6765
Epoch 90/200
2/2 [=====] - 0s 4ms/step - loss: 1.1877 - accuracy: 0.6471
Epoch 91/200
2/2 [=====] - 0s 5ms/step - loss: 1.1603 - accuracy: 0.6765
Epoch 92/200
2/2 [=====] - 0s 6ms/step - loss: 1.1398 - accuracy: 0.7353
Epoch 93/200
2/2 [=====] - 0s 4ms/step - loss: 1.1215 - accuracy: 0.6471
Epoch 94/200
2/2 [=====] - 0s 4ms/step - loss: 1.1028 - accuracy: 0.6471
Epoch 95/200
2/2 [=====] - 0s 4ms/step - loss: 1.0773 - accuracy: 0.7059
Epoch 96/200
2/2 [=====] - 0s 4ms/step - loss: 1.0495 - accuracy: 0.7353
Epoch 97/200
2/2 [=====] - 0s 5ms/step - loss: 1.0164 - accuracy: 0.7647
Epoch 98/200
2/2 [=====] - 0s 4ms/step - loss: 0.9861 - accuracy: 0.7647
Epoch 99/200

2/2 [=====] - 0s 4ms/step - loss: 0.9608 - accuracy: 0.7353
Epoch 100/200
2/2 [=====] - 0s 5ms/step - loss: 0.9370 - accuracy: 0.7353
Epoch 101/200
2/2 [=====] - 0s 4ms/step - loss: 0.9170 - accuracy: 0.7647
Epoch 102/200
2/2 [=====] - 0s 5ms/step - loss: 0.8931 - accuracy: 0.7353
Epoch 103/200
2/2 [=====] - 0s 5ms/step - loss: 0.8726 - accuracy: 0.7941
Epoch 104/200
2/2 [=====] - 0s 4ms/step - loss: 0.8485 - accuracy: 0.8235
Epoch 105/200
2/2 [=====] - 0s 4ms/step - loss: 0.8299 - accuracy: 0.8235
Epoch 106/200
2/2 [=====] - 0s 4ms/step - loss: 0.8118 - accuracy: 0.7941
Epoch 107/200
2/2 [=====] - 0s 5ms/step - loss: 0.7897 - accuracy: 0.7647
Epoch 108/200
2/2 [=====] - 0s 4ms/step - loss: 0.7610 - accuracy: 0.8529
Epoch 109/200
2/2 [=====] - 0s 4ms/step - loss: 0.7359 - accuracy: 0.8824
Epoch 110/200
2/2 [=====] - 0s 4ms/step - loss: 0.7151 - accuracy: 0.8824
Epoch 111/200
2/2 [=====] - 0s 5ms/step - loss: 0.7002 - accuracy: 0.8824
Epoch 112/200
2/2 [=====] - 0s 5ms/step - loss: 0.6869 - accuracy: 0.8529
Epoch 113/200
2/2 [=====] - 0s 5ms/step - loss: 0.6746 - accuracy: 0.8529
Epoch 114/200
2/2 [=====] - 0s 5ms/step - loss: 0.6585 - accuracy: 0.8824
Epoch 115/200
2/2 [=====] - 0s 4ms/step - loss: 0.6416 - accuracy: 0.8824
Epoch 116/200
2/2 [=====] - 0s 4ms/step - loss: 0.6259 - accuracy: 0.8529
Epoch 117/200
2/2 [=====] - 0s 5ms/step - loss: 0.6151 - accuracy: 0.8235
Epoch 118/200
2/2 [=====] - 0s 5ms/step - loss: 0.6096 - accuracy: 0.8529

Epoch 119/200
2/2 [=====] - 0s 5ms/step - loss: 0.5996 - accuracy: 0.8529
Epoch 120/200
2/2 [=====] - 0s 5ms/step - loss: 0.5900 - accuracy: 0.8529
Epoch 121/200
2/2 [=====] - 0s 5ms/step - loss: 0.5838 - accuracy: 0.8529
Epoch 122/200
2/2 [=====] - 0s 4ms/step - loss: 0.5671 - accuracy: 0.9118
Epoch 123/200
2/2 [=====] - 0s 4ms/step - loss: 0.5477 - accuracy: 0.9118
Epoch 124/200
2/2 [=====] - 0s 5ms/step - loss: 0.5283 - accuracy: 0.9118
Epoch 125/200
2/2 [=====] - 0s 5ms/step - loss: 0.5089 - accuracy: 0.9412
Epoch 126/200
2/2 [=====] - 0s 5ms/step - loss: 0.4923 - accuracy: 0.9412
Epoch 127/200
2/2 [=====] - 0s 4ms/step - loss: 0.4824 - accuracy: 0.9412
Epoch 128/200
2/2 [=====] - 0s 6ms/step - loss: 0.4719 - accuracy: 0.9118
Epoch 129/200
2/2 [=====] - 0s 4ms/step - loss: 0.4604 - accuracy: 0.9118
Epoch 130/200
2/2 [=====] - 0s 4ms/step - loss: 0.4495 - accuracy: 0.9118
Epoch 131/200
2/2 [=====] - 0s 4ms/step - loss: 0.4395 - accuracy: 0.9118
Epoch 132/200
2/2 [=====] - 0s 5ms/step - loss: 0.4290 - accuracy: 0.8824
Epoch 133/200
2/2 [=====] - 0s 4ms/step - loss: 0.4181 - accuracy: 0.8824
Epoch 134/200
2/2 [=====] - 0s 4ms/step - loss: 0.4088 - accuracy: 0.8824
Epoch 135/200
2/2 [=====] - 0s 4ms/step - loss: 0.4003 - accuracy: 0.9412
Epoch 136/200
2/2 [=====] - 0s 5ms/step - loss: 0.3955 - accuracy: 0.9412
Epoch 137/200
2/2 [=====] - 0s 4ms/step - loss: 0.3897 - accuracy: 0.8529
Epoch 138/200
2/2 [=====] - 0s 4ms/step - loss: 0.3877 - accuracy:

cy: 0.8824
Epoch 139/200
2/2 [=====] - 0s 4ms/step - loss: 0.3865 - accuracy: 0.8529
Epoch 140/200
2/2 [=====] - 0s 5ms/step - loss: 0.3853 - accuracy: 0.9118
Epoch 141/200
2/2 [=====] - 0s 4ms/step - loss: 0.3803 - accuracy: 0.9118
Epoch 142/200
2/2 [=====] - 0s 4ms/step - loss: 0.3717 - accuracy: 0.9412
Epoch 143/200
2/2 [=====] - 0s 4ms/step - loss: 0.3635 - accuracy: 0.9118
Epoch 144/200
2/2 [=====] - 0s 4ms/step - loss: 0.3580 - accuracy: 0.9118
Epoch 145/200
2/2 [=====] - 0s 5ms/step - loss: 0.3514 - accuracy: 0.8824
Epoch 146/200
2/2 [=====] - 0s 4ms/step - loss: 0.3428 - accuracy: 0.8824
Epoch 147/200
2/2 [=====] - 0s 4ms/step - loss: 0.3314 - accuracy: 0.9118
Epoch 148/200
2/2 [=====] - 0s 4ms/step - loss: 0.3259 - accuracy: 0.9118
Epoch 149/200
2/2 [=====] - 0s 5ms/step - loss: 0.3163 - accuracy: 0.8824
Epoch 150/200
2/2 [=====] - 0s 5ms/step - loss: 0.3100 - accuracy: 0.9118
Epoch 151/200
2/2 [=====] - 0s 4ms/step - loss: 0.3049 - accuracy: 0.9118
Epoch 152/200
2/2 [=====] - 0s 4ms/step - loss: 0.2994 - accuracy: 0.9118
Epoch 153/200
2/2 [=====] - 0s 4ms/step - loss: 0.2920 - accuracy: 0.9118
Epoch 154/200
2/2 [=====] - 0s 4ms/step - loss: 0.2775 - accuracy: 0.9118
Epoch 155/200
2/2 [=====] - 0s 5ms/step - loss: 0.2645 - accuracy: 0.9118
Epoch 156/200
2/2 [=====] - 0s 4ms/step - loss: 0.2571 - accuracy: 0.9412
Epoch 157/200
2/2 [=====] - 0s 4ms/step - loss: 0.2510 - accuracy: 0.9412
Epoch 158/200

2/2 [=====] - 0s 4ms/step - loss: 0.2466 - accuracy: 0.9706
Epoch 159/200
2/2 [=====] - 0s 4ms/step - loss: 0.2408 - accuracy: 0.9706
Epoch 160/200
2/2 [=====] - 0s 4ms/step - loss: 0.2345 - accuracy: 1.0000
Epoch 161/200
2/2 [=====] - 0s 4ms/step - loss: 0.2274 - accuracy: 1.0000
Epoch 162/200
2/2 [=====] - 0s 4ms/step - loss: 0.2215 - accuracy: 1.0000
Epoch 163/200
2/2 [=====] - 0s 4ms/step - loss: 0.2152 - accuracy: 1.0000
Epoch 164/200
2/2 [=====] - 0s 4ms/step - loss: 0.2091 - accuracy: 1.0000
Epoch 165/200
2/2 [=====] - 0s 5ms/step - loss: 0.2034 - accuracy: 1.0000
Epoch 166/200
2/2 [=====] - 0s 4ms/step - loss: 0.1991 - accuracy: 1.0000
Epoch 167/200
2/2 [=====] - 0s 4ms/step - loss: 0.1926 - accuracy: 1.0000
Epoch 168/200
2/2 [=====] - 0s 5ms/step - loss: 0.1884 - accuracy: 1.0000
Epoch 169/200
2/2 [=====] - 0s 5ms/step - loss: 0.1856 - accuracy: 1.0000
Epoch 170/200
2/2 [=====] - 0s 5ms/step - loss: 0.1845 - accuracy: 1.0000
Epoch 171/200
2/2 [=====] - 0s 4ms/step - loss: 0.1873 - accuracy: 0.9706
Epoch 172/200
2/2 [=====] - 0s 5ms/step - loss: 0.1934 - accuracy: 0.9706
Epoch 173/200
2/2 [=====] - 0s 5ms/step - loss: 0.1990 - accuracy: 0.9118
Epoch 174/200
2/2 [=====] - 0s 4ms/step - loss: 0.2012 - accuracy: 0.9118
Epoch 175/200
2/2 [=====] - 0s 5ms/step - loss: 0.1981 - accuracy: 0.9118
Epoch 176/200
2/2 [=====] - 0s 4ms/step - loss: 0.1921 - accuracy: 0.9118
Epoch 177/200
2/2 [=====] - 0s 5ms/step - loss: 0.1842 - accuracy: 0.9412

Epoch 178/200
2/2 [=====] - 0s 5ms/step - loss: 0.1758 - accuracy: 0.9706
Epoch 179/200
2/2 [=====] - 0s 4ms/step - loss: 0.1674 - accuracy: 0.9706
Epoch 180/200
2/2 [=====] - 0s 4ms/step - loss: 0.1599 - accuracy: 0.9706
Epoch 181/200
2/2 [=====] - 0s 4ms/step - loss: 0.1582 - accuracy: 0.9706
Epoch 182/200
2/2 [=====] - 0s 4ms/step - loss: 0.1619 - accuracy: 0.9706
Epoch 183/200
2/2 [=====] - 0s 5ms/step - loss: 0.1653 - accuracy: 0.9706
Epoch 184/200
2/2 [=====] - 0s 5ms/step - loss: 0.1593 - accuracy: 0.9706
Epoch 185/200
2/2 [=====] - 0s 4ms/step - loss: 0.1546 - accuracy: 0.9706
Epoch 186/200
2/2 [=====] - 0s 4ms/step - loss: 0.1595 - accuracy: 0.9412
Epoch 187/200
2/2 [=====] - 0s 4ms/step - loss: 0.1682 - accuracy: 0.9412
Epoch 188/200
2/2 [=====] - 0s 5ms/step - loss: 0.1730 - accuracy: 0.9412
Epoch 189/200
2/2 [=====] - 0s 4ms/step - loss: 0.1718 - accuracy: 0.9412
Epoch 190/200
2/2 [=====] - 0s 4ms/step - loss: 0.1660 - accuracy: 0.9412
Epoch 191/200
2/2 [=====] - 0s 5ms/step - loss: 0.1569 - accuracy: 0.9412
Epoch 192/200
2/2 [=====] - 0s 4ms/step - loss: 0.1465 - accuracy: 0.9412
Epoch 193/200
2/2 [=====] - 0s 5ms/step - loss: 0.1364 - accuracy: 0.9706
Epoch 194/200
2/2 [=====] - 0s 4ms/step - loss: 0.1276 - accuracy: 0.9706
Epoch 195/200
2/2 [=====] - 0s 5ms/step - loss: 0.1220 - accuracy: 0.9706
Epoch 196/200
2/2 [=====] - 0s 5ms/step - loss: 0.1170 - accuracy: 0.9706
Epoch 197/200
2/2 [=====] - 0s 4ms/step - loss: 0.1156 - accuracy:

```
cy: 0.9706
Epoch 198/200
2/2 [=====] - 0s 4ms/step - loss: 0.1093 - accuracy: 1.0000
Epoch 199/200
2/2 [=====] - 0s 5ms/step - loss: 0.1056 - accuracy: 1.0000
Epoch 200/200
2/2 [=====] - 0s 4ms/step - loss: 0.1119 - accuracy: 0.9706
```

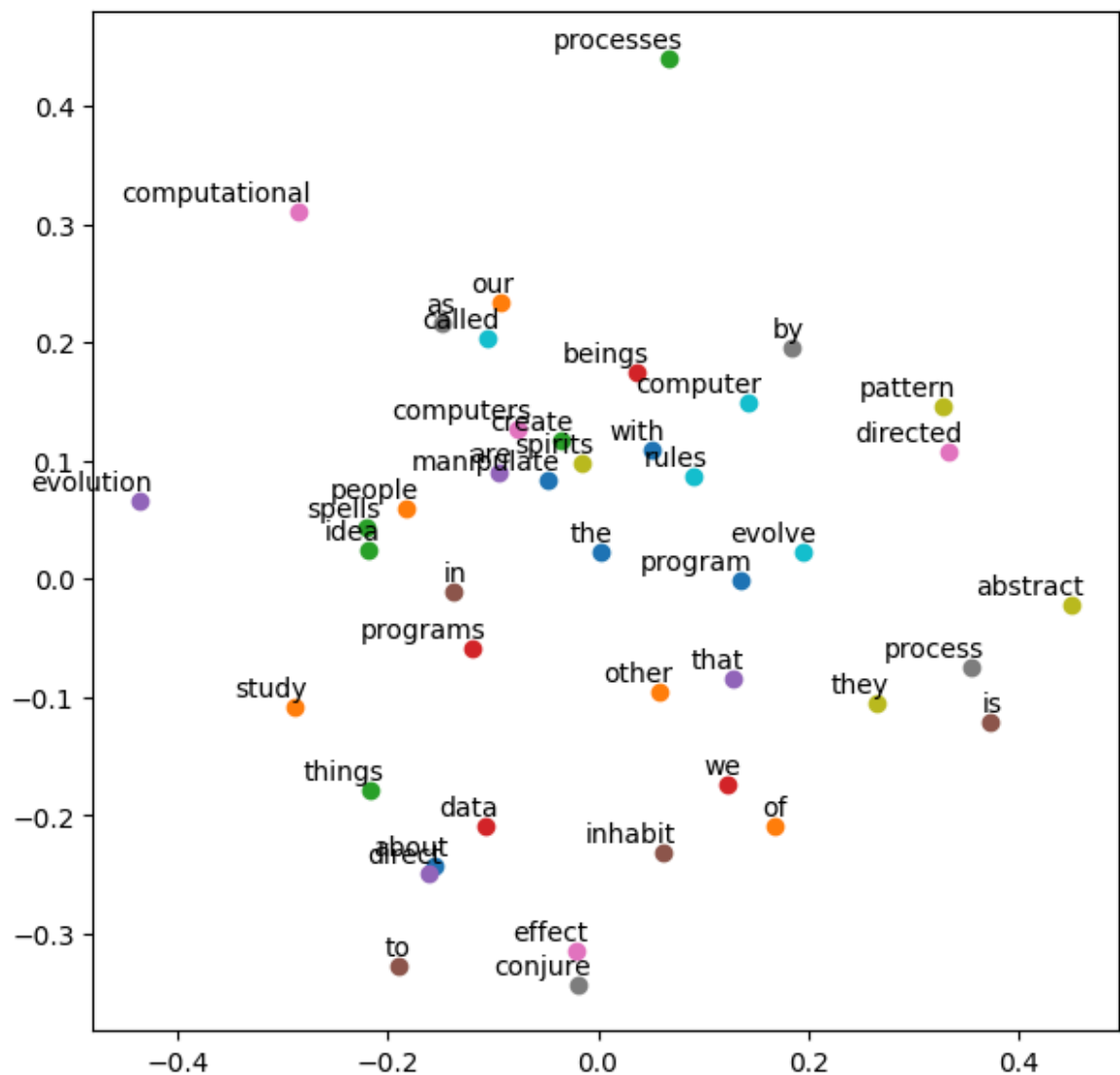
Out[15]: <keras.src.callbacks.History at 0x7f9a47db7690>

```
In [16]: # Get the word embeddings
embeddings = model.get_weights()[0]

# Perform PCA to reduce the dimensionality of the embeddings
pca = PCA(n_components=2)
reduced_embeddings = pca.fit_transform(embeddings)
```

d. Output

```
In [17]: # Visualize the embeddings
plt.figure(figsize=(7, 7))
for i, word in enumerate(tokenizer.word_index.keys()):
    x, y = reduced_embeddings[i]
    plt.scatter(x, y)
    plt.annotate(word, xy=(x, y), xytext=(5, 2),
                  textcoords='offset points',
                  ha='right', va='bottom')
plt.show()
```



```
In [18]: # test model
test_sentences = [
    "we are to study",
    "create programs direct processes",
    "spirits process study program",
    "idea study people create"
]
```

```
In [19]: for test_sentence in test_sentences:
    test_words = test_sentence.split(" ")
    print("Words: ", test_words)
    x_test = []
    for i in test_words:
        x_test.append(word_to_index_map.get(i))
    x_test = np.array([x_test])
    print("Indexes: ", x_test)
    test_predictions = model.predict(x_test)
    y_pred = np.argmax(test_predictions[0])
    print("Predictions: ", test_words, " => ", index_to_word_map.get(y_pred))
    print("\n")
```


Words: ['we', 'are', 'to', 'study']
Indexs: [[4 5 6 12]]
1/1 [=====] - 0s 58ms/step
Predictions: ['we', 'are', 'to', 'study'] => about

Words: ['create', 'programs', 'direct', 'processes']
Indexs: [[33 34 35 3]]
1/1 [=====] - 0s 14ms/step
Predictions: ['create', 'programs', 'direct', 'processes'] => to

Words: ['spirits', 'process', 'study', 'program']
Indexs: [[39 8 12 31]]
1/1 [=====] - 0s 13ms/step
Predictions: ['spirits', 'process', 'study', 'program'] => are

Words: ['idea', 'study', 'people', 'create']
Indexs: [[13 12 32 33]]
1/1 [=====] - 0s 13ms/step
Predictions: ['idea', 'study', 'people', 'create'] => programs