

# 5: Continuous Bag of Words (CBOW) Model Implementation for text recognition # -----  
----- # a) Data preparation # b) Generate training data # c) Train model # d) Output # -----  
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In [1]: *# a) Data Preparation*

```
import numpy as np
import tensorflow as tf
from tensorflow.keras import layers, models, optimizers
print("Imports complete!\n")

# Demo text
raw_text = ""Machine learning enables computers to discover patterns from data.
Neural networks are powerful models that learn representations automatically.
Natural language processing allows machines to understand human communication.
Deep learning methods are transforming artificial intelligence research and appl

vocab = sorted(set(raw_text))
vocab_size = len(vocab)
word_to_ix = {word: ix for ix, word in enumerate(vocab)}
ix_to_word = {ix: word for word, ix in word_to_ix.items()}

print("Vocabulary size:", vocab_size)
print("First 5 word-index pairs:", list(word_to_ix.items())[:5])
```

Imports complete!

Vocabulary size: 34

First 5 word-index pairs: [('Deep', 0), ('Machine', 1), ('Natural', 2), ('Neural', 3), ('allows', 4)]

In [2]: *# b) Generate Training Data*

```
CONTEXT_SIZE = 2          # Two words before, two after
EMBEDDING_DIM = 50        # Size of word embedding vectors

def make_context_vector(context, word_to_ix):
    return [word_to_ix[w] for w in context]

data = []
for i in range(CONTEXT_SIZE, len(raw_text) - CONTEXT_SIZE):
    context = [
        raw_text[i - 2], raw_text[i - 1],
        raw_text[i + 1], raw_text[i + 2]
    ]
    target = raw_text[i]
    data.append((context, target))

X = np.array([make_context_vector(ctx, word_to_ix) for ctx, _ in data])
y = np.array([word_to_ix[target] for _, target in data])

print("Shape of X (contexts):", X.shape)
print("Shape of y (targets):", y.shape)
print("Sample context/target:\n Context:", [vocab[ix] for ix in X[0]], "\n Tar
```

Shape of X (contexts): (33, 4)

Shape of y (targets): (33,)

Sample context/target:

Context: ['Machine', 'learning', 'computers', 'to']

Target: enables

In [3]: `# c) Define CBOW model in Keras`

```
inputs = layers.Input(shape=(4,), dtype="int32") # 4 context words (indices)
embed = layers.Embedding(input_dim=vocab_size, output_dim=EMBEDDING_DIM)(inputs)
avg_embed = layers.Lambda(lambda x: tf.reduce_mean(x, axis=1))(embed)
dense1 = layers.Dense(128, activation="relu")(avg_embed)
outputs = layers.Dense(vocab_size, activation="softmax")(dense1)

cbow_model = models.Model(inputs=inputs, outputs=outputs)
cbow_model.compile(
    optimizer=optimizers.Adam(learning_rate=0.01),
    loss="sparse_categorical_crossentropy",
    metrics=["accuracy"]
)
print("CBOW model summary:")
cbow_model.summary()
```

WARNING:tensorflow:From C:\Users\kusha\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.12\_qbz5n2kfra8p0\LocalCache\local-packages\Python312\site-packages\keras\src\backend\tensorflow\core.py:219: The name tf.placeholder is deprecated. Please use tf.compat.v1.placeholder instead.

CBOW model summary:  
**Model: "functional"**

Layer (type)	Output Shape	
input_layer ( <a href="#">InputLayer</a> )	(None, 4)	
embedding ( <a href="#">Embedding</a> )	(None, 4, 50)	
lambda ( <a href="#">Lambda</a> )	(None, 50)	
dense ( <a href="#">Dense</a> )	(None, 128)	
dense_1 ( <a href="#">Dense</a> )	(None, 34)	








**Total params:** 12,614 (49.27 KB)

**Trainable params:** 12,614 (49.27 KB)

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

In [4]: `# d) Train the model`

```
history = cbow_model.fit(
    X, y,
    epochs=100,
    batch_size=8,
    verbose=1
)
print("Training done!\n")
```

Epoch 1/100  
5/5  1s 8ms/step - accuracy: 0.0000e+00 - loss: 3.5421  
Epoch 2/100  
5/5  0s 7ms/step - accuracy: 0.1717 - loss: 3.4669  
Epoch 3/100  
5/5  0s 7ms/step - accuracy: 0.2524 - loss: 3.3259  
Epoch 4/100  
5/5  0s 7ms/step - accuracy: 0.3542 - loss: 3.0758  
Epoch 5/100  
5/5  0s 7ms/step - accuracy: 0.3389 - loss: 2.6599  
Epoch 6/100  
5/5  0s 6ms/step - accuracy: 0.4129 - loss: 2.1166  
Epoch 7/100  
5/5  0s 7ms/step - accuracy: 0.5843 - loss: 1.6756  
Epoch 8/100  
5/5  0s 7ms/step - accuracy: 0.6282 - loss: 1.1565  
Epoch 9/100  
5/5  0s 7ms/step - accuracy: 0.8450 - loss: 0.7872  
Epoch 10/100  
5/5  0s 7ms/step - accuracy: 0.9676 - loss: 0.5244  
Epoch 11/100  
5/5  0s 6ms/step - accuracy: 0.9673 - loss: 0.3197  
Epoch 12/100  
5/5  0s 7ms/step - accuracy: 0.9777 - loss: 0.1864  
Epoch 13/100  
5/5  0s 6ms/step - accuracy: 1.0000 - loss: 0.1278  
Epoch 14/100  
5/5  0s 7ms/step - accuracy: 1.0000 - loss: 0.0686  
Epoch 15/100  
5/5  0s 7ms/step - accuracy: 1.0000 - loss: 0.0391  
Epoch 16/100  
5/5  0s 6ms/step - accuracy: 1.0000 - loss: 0.0324  
Epoch 17/100  
5/5  0s 6ms/step - accuracy: 1.0000 - loss: 0.0211  
Epoch 18/100  
5/5  0s 7ms/step - accuracy: 1.0000 - loss: 0.0157  
Epoch 19/100  
5/5  0s 7ms/step - accuracy: 1.0000 - loss: 0.0134  
Epoch 20/100  
5/5  0s 7ms/step - accuracy: 1.0000 - loss: 0.0116  
Epoch 21/100  
5/5  0s 7ms/step - accuracy: 1.0000 - loss: 0.0100  
Epoch 22/100  
5/5  0s 6ms/step - accuracy: 1.0000 - loss: 0.0069  
Epoch 23/100  
5/5  0s 7ms/step - accuracy: 1.0000 - loss: 0.0067  
Epoch 24/100  
5/5  0s 7ms/step - accuracy: 1.0000 - loss: 0.0063  
Epoch 25/100  
5/5  0s 7ms/step - accuracy: 1.0000 - loss: 0.0052  
Epoch 26/100  
5/5  0s 7ms/step - accuracy: 1.0000 - loss: 0.0049  
Epoch 27/100  
5/5  0s 7ms/step - accuracy: 1.0000 - loss: 0.0044  
Epoch 28/100  
5/5  0s 7ms/step - accuracy: 1.0000 - loss: 0.0039  
Epoch 29/100  
5/5  0s 7ms/step - accuracy: 1.0000 - loss: 0.0035  
Epoch 30/100  
5/5  0s 8ms/step - accuracy: 1.0000 - loss: 0.0037

Epoch 31/100  
5/5  0s 7ms/step - accuracy: 1.0000 - loss: 0.0033  
Epoch 32/100  
5/5  0s 7ms/step - accuracy: 1.0000 - loss: 0.0029  
Epoch 33/100  
5/5  0s 7ms/step - accuracy: 1.0000 - loss: 0.0027  
Epoch 34/100  
5/5  0s 7ms/step - accuracy: 1.0000 - loss: 0.0030  
Epoch 35/100  
5/5  0s 7ms/step - accuracy: 1.0000 - loss: 0.0026  
Epoch 36/100  
5/5  0s 6ms/step - accuracy: 1.0000 - loss: 0.0024  
Epoch 37/100  
5/5  0s 7ms/step - accuracy: 1.0000 - loss: 0.0024  
Epoch 38/100  
5/5  0s 8ms/step - accuracy: 1.0000 - loss: 0.0021  
Epoch 39/100  
5/5  0s 8ms/step - accuracy: 1.0000 - loss: 0.0022  
Epoch 40/100  
5/5  0s 7ms/step - accuracy: 1.0000 - loss: 0.0021  
Epoch 41/100  
5/5  0s 7ms/step - accuracy: 1.0000 - loss: 0.0020  
Epoch 42/100  
5/5  0s 7ms/step - accuracy: 1.0000 - loss: 0.0019  
Epoch 43/100  
5/5  0s 7ms/step - accuracy: 1.0000 - loss: 0.0019  
Epoch 44/100  
5/5  0s 7ms/step - accuracy: 1.0000 - loss: 0.0017  
Epoch 45/100  
5/5  0s 7ms/step - accuracy: 1.0000 - loss: 0.0017  
Epoch 46/100  
5/5  0s 7ms/step - accuracy: 1.0000 - loss: 0.0016  
Epoch 47/100  
5/5  0s 7ms/step - accuracy: 1.0000 - loss: 0.0015  
Epoch 48/100  
5/5  0s 8ms/step - accuracy: 1.0000 - loss: 0.0015  
Epoch 49/100  
5/5  0s 7ms/step - accuracy: 1.0000 - loss: 0.0013  
Epoch 50/100  
5/5  0s 7ms/step - accuracy: 1.0000 - loss: 0.0014  
Epoch 51/100  
5/5  0s 7ms/step - accuracy: 1.0000 - loss: 0.0014  
Epoch 52/100  
5/5  0s 6ms/step - accuracy: 1.0000 - loss: 0.0013  
Epoch 53/100  
5/5  0s 7ms/step - accuracy: 1.0000 - loss: 0.0012  
Epoch 54/100  
5/5  0s 7ms/step - accuracy: 1.0000 - loss: 0.0011  
Epoch 55/100  
5/5  0s 6ms/step - accuracy: 1.0000 - loss: 0.0011  
Epoch 56/100  
5/5  0s 7ms/step - accuracy: 1.0000 - loss: 0.0011  
Epoch 57/100  
5/5  0s 7ms/step - accuracy: 1.0000 - loss: 0.0011  
Epoch 58/100  
5/5  0s 7ms/step - accuracy: 1.0000 - loss: 0.0011  
Epoch 59/100  
5/5  0s 6ms/step - accuracy: 1.0000 - loss: 9.6663e-04  
Epoch 60/100  
5/5  0s 6ms/step - accuracy: 1.0000 - loss: 0.0010

Epoch 61/100  
5/5  0s 6ms/step - accuracy: 1.0000 - loss: 9.5311e-04  
Epoch 62/100  
5/5  0s 7ms/step - accuracy: 1.0000 - loss: 9.1310e-04  
Epoch 63/100  
5/5  0s 6ms/step - accuracy: 1.0000 - loss: 8.3330e-04  
Epoch 64/100  
5/5  0s 6ms/step - accuracy: 1.0000 - loss: 8.5978e-04  
Epoch 65/100  
5/5  0s 7ms/step - accuracy: 1.0000 - loss: 7.8530e-04  
Epoch 66/100  
5/5  0s 7ms/step - accuracy: 1.0000 - loss: 8.6450e-04  
Epoch 67/100  
5/5  0s 6ms/step - accuracy: 1.0000 - loss: 7.9345e-04  
Epoch 68/100  
5/5  0s 7ms/step - accuracy: 1.0000 - loss: 7.8645e-04  
Epoch 69/100  
5/5  0s 7ms/step - accuracy: 1.0000 - loss: 7.2354e-04  
Epoch 70/100  
5/5  0s 6ms/step - accuracy: 1.0000 - loss: 7.3858e-04  
Epoch 71/100  
5/5  0s 7ms/step - accuracy: 1.0000 - loss: 7.4215e-04  
Epoch 72/100  
5/5  0s 7ms/step - accuracy: 1.0000 - loss: 7.1911e-04  
Epoch 73/100  
5/5  0s 9ms/step - accuracy: 1.0000 - loss: 6.3773e-04  
Epoch 74/100  
5/5  0s 7ms/step - accuracy: 1.0000 - loss: 6.3913e-04  
Epoch 75/100  
5/5  0s 8ms/step - accuracy: 1.0000 - loss: 6.2974e-04  
Epoch 76/100  
5/5  0s 7ms/step - accuracy: 1.0000 - loss: 6.4009e-04  
Epoch 77/100  
5/5  0s 7ms/step - accuracy: 1.0000 - loss: 6.1528e-04  
Epoch 78/100  
5/5  0s 6ms/step - accuracy: 1.0000 - loss: 5.9539e-04  
Epoch 79/100  
5/5  0s 6ms/step - accuracy: 1.0000 - loss: 5.4058e-04  
Epoch 80/100  
5/5  0s 6ms/step - accuracy: 1.0000 - loss: 5.6306e-04  
Epoch 81/100  
5/5  0s 7ms/step - accuracy: 1.0000 - loss: 5.9318e-04  
Epoch 82/100  
5/5  0s 7ms/step - accuracy: 1.0000 - loss: 5.3875e-04  
Epoch 83/100  
5/5  0s 7ms/step - accuracy: 1.0000 - loss: 5.0996e-04  
Epoch 84/100  
5/5  0s 7ms/step - accuracy: 1.0000 - loss: 5.4855e-04  
Epoch 85/100  
5/5  0s 7ms/step - accuracy: 1.0000 - loss: 4.8467e-04  
Epoch 86/100  
5/5  0s 7ms/step - accuracy: 1.0000 - loss: 4.9387e-04  
Epoch 87/100  
5/5  0s 7ms/step - accuracy: 1.0000 - loss: 4.6639e-04  
Epoch 88/100  
5/5  0s 7ms/step - accuracy: 1.0000 - loss: 4.6948e-04  
Epoch 89/100  
5/5  0s 7ms/step - accuracy: 1.0000 - loss: 4.4877e-04  
Epoch 90/100  
5/5  0s 7ms/step - accuracy: 1.0000 - loss: 4.3608e-04

```

Epoch 91/100
5/5 ————— 0s 7ms/step - accuracy: 1.0000 - loss: 4.4905e-04
Epoch 92/100
5/5 ————— 0s 6ms/step - accuracy: 1.0000 - loss: 4.5017e-04
Epoch 93/100
5/5 ————— 0s 7ms/step - accuracy: 1.0000 - loss: 4.0377e-04
Epoch 94/100
5/5 ————— 0s 6ms/step - accuracy: 1.0000 - loss: 4.3544e-04
Epoch 95/100
5/5 ————— 0s 7ms/step - accuracy: 1.0000 - loss: 3.8707e-04
Epoch 96/100
5/5 ————— 0s 7ms/step - accuracy: 1.0000 - loss: 3.9527e-04
Epoch 97/100
5/5 ————— 0s 7ms/step - accuracy: 1.0000 - loss: 4.0421e-04
Epoch 98/100
5/5 ————— 0s 6ms/step - accuracy: 1.0000 - loss: 3.8319e-04
Epoch 99/100
5/5 ————— 0s 7ms/step - accuracy: 1.0000 - loss: 3.6891e-04
Epoch 100/100
5/5 ————— 0s 6ms/step - accuracy: 1.0000 - loss: 3.7637e-04
Training done!

```

In [5]: *# e) Output: Test context for prediction*

```

test_context = ['Neural', 'networks', 'that', 'learn']
test_input = np.array([make_context_vector(test_context, word_to_ix)])
pred_probs = cbow_model.predict(test_input)
pred_idx = np.argmax(pred_probs[0])
pred_word = ix_to_word[pred_idx]

print("\n-----")
print("Test Context Words:", test_context)
print("Predicted Target Word:", pred_word)
print("-----")

```

```

1/1 ————— 0s 74ms/step

```

```

-----
Test Context Words: ['Neural', 'networks', 'that', 'learn']
Predicted Target Word: models
-----

```