

Title: CBOW (Continuous Bag of Words) - Full Walkthrough with Manual Math Explanation

Objective:

To manually demonstrate how CBOW (Continuous Bag of Words) learns word embeddings using simple sentence, step-by-step math, and logic suitable for Humanities and Social Sciences (HSS) students.

Example Sentence (Tiny Corpus):

"the cat sat on the mat"

Vocabulary: [the, cat, sat, on, mat, dog]

Index assignment:

Word Index

the 0

cat 1

sat 2

on 3

mat 4

dog 5

We use:

- Embedding size = **2**
 - Context window size = **1**
-

Task:

Given context words cat and on, predict the center word: sat

✅ Step 1: One-Hot Encode the Context Words

One-hot vector for "cat" (index 1): [0, 1, 0, 0, 0, 0] One-hot vector for "on" (index 3): [0, 0, 0, 1, 0, 0]

Add them:

$$[0, 1, 0, 0, 0, 0] + [0, 0, 0, 1, 0, 0] = [0, 1, 0, 1, 0, 0]$$

Average them:

$$[0, 1, 0, 1, 0, 0] / 2 = [0, 0.5, 0, 0.5, 0, 0]$$

This is our input vector.

✅ Step 2: Input Embedding Matrix W (6x2)

Each row corresponds to a word vector of size 2. These numbers are **randomly initialized** when training starts. They do not represent meaning yet. The training process will adjust them to become meaningful based on context.

Word dim1 dim2

the 0.1 0.3

cat 0.2 0.4

sat 0.0 0.5

on 0.6 0.1

mat 0.3 0.7

dog 0.2 0.2

We retrieve vectors for cat and on:

- cat = [0.2, 0.4]
- on = [0.6, 0.1]

Average them:

$$([0.2 + 0.6] / 2, [0.4 + 0.1] / 2) = [0.4, 0.25] \leftarrow \text{hidden layer output}$$

✅ Step 3: Output Weight Matrix W' (2x6)

Transpose: now columns represent words

the cat sat on mat dog

dim1 0.3 0.2 0.4 0.6 0.1 0.7

dim2 0.5 0.3 0.2 0.4 0.6 0.2

Multiply [0.4, 0.25] with each column (dot product):

Word	Calculation	Output
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the	$0.4 \cdot (0.3) + 0.25 \cdot (0.5) = 0.12 + 0.125$	0.245
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cat	$0.4 \cdot (0.2) + 0.25 \cdot (0.3) = 0.08 + 0.075$	0.155
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sat	$0.4 \cdot (0.4) + 0.25 \cdot (0.2) = 0.16 + 0.05$	0.21
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on	$0.4 \cdot (0.6) + 0.25 \cdot (0.4) = 0.24 + 0.1$	0.34
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mat	$0.4 \cdot (0.1) + 0.25 \cdot (0.6) = 0.04 + 0.15$	0.19
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dog	$0.4 \cdot (0.7) + 0.25 \cdot (0.2) = 0.28 + 0.05$	0.33
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✅ Step 4: Apply Softmax

Exponentiate all outputs (using e^x):

Word e^{score}

the $e^{0.245} \approx 1.277$

cat $e^{0.155} \approx 1.167$

sat $e^{0.210} \approx 1.233$

on $e^{0.340} \approx 1.405$

mat $e^{0.190} \approx 1.209$

dog $e^{0.330} \approx 1.391$

Sum = $1.277 + 1.167 + 1.233 + 1.405 + 1.209 + 1.391 \approx 7.682$

Now divide each by the total (normalize):

Word Softmax Probability

the $1.277 / 7.682 \approx 0.166$

cat $1.167 / 7.682 \approx 0.152$

sat $1.233 / 7.682 \approx 0.160 \leftarrow$ correct word!

on $1.405 / 7.682 \approx 0.183$

mat $1.209 / 7.682 \approx 0.157$

dog $1.391 / 7.682 \approx 0.181$

✅ Step 5: Compute Loss

We use **Cross-Entropy Loss** to measure how far our prediction is from the correct answer.

We predicted probabilities using softmax. The probability of the correct word "sat" was **0.160**.

So the loss becomes:

$$\begin{aligned}\text{Loss} &= -\log(\text{probability of correct word}) \\ &= -\log(0.160) \approx 1.83\end{aligned}$$

🔴 How do we know this prediction is wrong?

- The original (raw) score before softmax for "sat" was **0.21** (from dot product).
- Softmax turned this into a probability: **0.160**.
- Since 0.160 is not very high (ideal = close to 1), it means the model isn't confident.

✅ Step 6: Backpropagation (with Gradient Descent)

📦 **Backpropagation** helps the model learn from mistakes:

1. **Error Calculation:** For each word:

- $\text{error} = \text{predicted_probability} - \text{actual}$
- Only "sat" is the correct word (actual = 1), others = 0.

2. Gradient Calculation:

- Gradients show how much each weight contributed to the error.
- Computed for both W and W' matrices.

3. Weight Updates:

- Each weight is adjusted using:

$\text{new_weight} = \text{old_weight} - \text{learning_rate} * \text{gradient}$

- This helps push the score for the correct word up (and wrong ones down).

Over many training steps, these weights (word vectors) become better at capturing the meaning/context of each word.
