Comparison Report - CBOW vs BERT

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1. Objective

Compare **static word embeddings (CBOW)** with **contextual embeddings (BERT)** using a simple classification task. We used a tiny labeled dataset containing two semantic categories:

- **Finance-related sentences**
- **Nature-related sentences**

Both CBOW and BERT embeddings were used as input features to a **Logistic Regression classifier**, and classification accuracy is measured.

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2. Test Setup

🔹 CBOW Representation

- Trained on a small corpus (Tiny Game of Thrones text).
- Embeddings are learned using average context window vectors (window size = 2).
- Word representation is static: every word has exactly one embedding vector.

🔹 BERT Representation

- Used pretrained **bert-base-uncased** model.
- Extracted sentence embeddings using the **CLS token (768-dim vector)**.
- Embeddings are contextual: representation depends on entire sentence meaning.

🔹 Classifier

- Logistic Regression
- Train/test split: 70/30
- Evaluation metric: **accuracy**

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3. Quantitative Results

Model	Type	Accuracy
CBOW	Static embeddings	**0.33**
BERT	Contextual embeddings	**1.00**

There is a **dramatic difference** in model performance.

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4. Observations

➢ CBOW

- Classification accuracy was close to random guessing.
- CBOW embeddings **failed to separate finance vs nature text**.
- Words like “bank” had the **same vector** in both sentences:
  - “The bank approved the loan.” ✔ finance
  - “Birds rested near the bank of the river.” ✔ nature
- CBOW does **not capture word meaning differences** based on context.

➢ BERT

- Classification accuracy was **perfect** (1.0).
- BERT produced **distinct embeddings** for sentences based on meaning.

- The Embedding of “bank” in finance and nature sentences was different.
- BERT processed **sentence structure, word order, and entire context**.

Explanation of Findings (Detailed)

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1. Static vs Contextual Embeddings

Property	**CBOW**	**BERT**
Context sensitivity	No	Yes
One vector per word	Yes	No
Handles polysemy	Poor	Excellent
Sentence-level info	None	Full Transformer encoding

Conclusion:
CBOW **ignores context**, while BERT **uses context to build meaning**.

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2. Polysemy Problem (Main Difference)

Polysemy = a word having multiple meanings.

Example:

- “bank" → financial institution
- “bank" → river side

CBOW

- One embedding for "bank"

- Cannot distinguish two meanings
- Classifier fails

BERT

- Creates different vectors:

bank(finance) → close to "loan", "money", "credit"
bank(nature) → close to "river", "trees", "forest"

That alone explains the **1.0 vs 0.33 performance gap**.

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3. Training Data Advantage

CBOW was trained only on a **tiny local corpus**.
BERT was trained on **millions of sentences** with deep semantics.

Thus, BERT has a built-in understanding of:

- economics
- geography
- general world knowledge

CBOW does not.

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4. Sentence Encoding

CBOW sentence embedding:

- **Average of word embeddings**
- Loses:

- grammar
- word order
- long range dependency

Example:

“The bank not loan issue will.” → same vector as the original sentence (roughly)

BERT sentence embedding:

- Uses **transformer attention**:
  - Attends to important words
  - Identifies semantic roles
  - Encodes relationships

Example:

"loan" strongly connected to "bank"
"river" strongly connected to "bank"
→ different sentence vectors

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5. Why BERT Classifier Works Perfectly

1. **Rich pretrained feature space**
2. **Contextual semantic separation**
3. **CLS vector contains sentence meaning**
4. **Small dataset is enough** (no training needed!)

Even with only 10 examples:

BERT = 100%
CBOW = 33%

Final Statement:

This experiment demonstrates that contextual embeddings significantly outperform static embeddings for semantic sentence classification tasks. While CBOW generates a single embedding for each word regardless of context, BERT generates different embeddings for the same word depending on surrounding text. In a binary classifier distinguishing finance-related and nature-related sentences, CBOW achieved 33% accuracy, indicating poor separability, whereas BERT achieved 100% accuracy, demonstrating strong semantic understanding. These results confirm that contextual word embeddings are superior for downstream NLP problems, especially where multiple meanings and contextual relationships are important.