# Word vectors

Jan 20, 2026

# Outline

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# Last class: What is NLP?

Natural Language Processing (NLP) is a subfield of computer science and artificial intelligence that develops computational methods for enabling computers to understand, interpret, and generate human language.

- What does it mean to understand human language?

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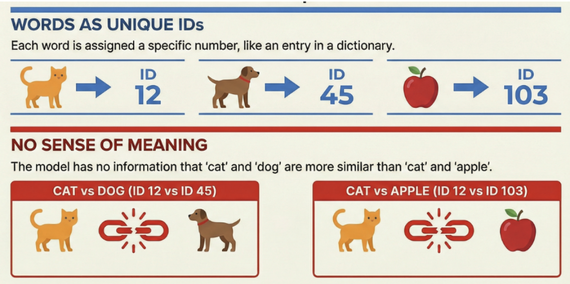
Natural Language Processing (NLP) is a subfield of computer science and artificial intelligence that develops computational methods for enabling computers to understand, interpret, and generate human language.

- What does it mean to understand human language?
- Q. How do we represent **meanings** in computer?

# Encoding: Background

- In traditional NLP, people treated words as discrete symbols.



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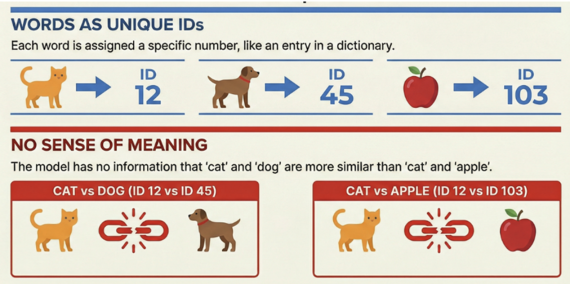


- Practically building/updating a database is expensive.

# Encoding

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- Words themselves cannot be given as inputs to computers
- **Numbers** can be.
- **Encoding**: converting words to numbers
- **Vector**: an ordered list of numbers (e.g., [0.1, 0.3, -0.5])

# One-hot encoding

- *The cat sat*

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- *The cat sat*

| word | encoding |
|---|---|
| the | [1, 0, 0] |
| cat | [0, 1, 0] |
| sat | [0, 0, 1] |

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- Only the entry for the word is set to 1.
- **Localist, sparse** representation

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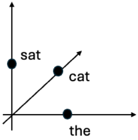

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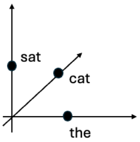

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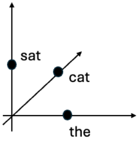


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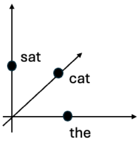


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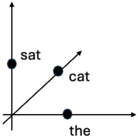


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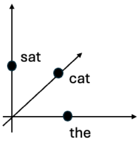


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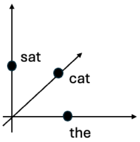


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- Still, words carry no information about meaning or similarity.
- All one-hot vectors are orthogonal (equally distant from each other)
- **Cosine similarity:**
  - $\cos(\theta) = \frac{\vec{A} \cdot \vec{B}}{\|\vec{A}\| \|\vec{B}\|}$

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# One-hot encoding: Solution

- Move from **sparse** to **distributed** representation

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- Move from **sparse** to **distributed** representation
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- Word **embeddings**

## Two viewpoints on meaning

There are different theoretical views on what it means to "know" the meaning of a word (Manning, 2022)

1. **Denotational semantics** Meaning is the set of objects, events, or situations in the world that a word or sentence refers to.

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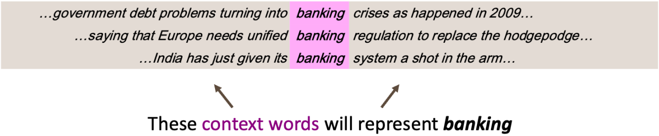
There are different theoretical views on what it means to "know" the meaning of a word (Manning, 2022)

1. **Denotational semantics** Meaning is the set of objects, events, or situations in the world that a word or sentence refers to.
2. **Distributional semantics** Meaning is characterized by the **contexts** in which a word appears.

# Meaning and language models

- Hypothesis: If meaning is defined as patterns of use and relations among words, then pretrained language models *do* learn meanings.

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| | | |
|---|---|---|
| *...government debt problems turning into* | ***banking*** | *crises as happened in 2009...* |
| *...saying that Europe needs unified* | ***banking*** | *regulation to replace the hodgepodge...* |
| *...India has just given its* | ***banking*** | *system a shot in the arm...* |

These context words will represent ***banking***

- "You shall know a word by the company it keeps" (Firth, 1957): One of the most successful ideas of modern statistical NLP.

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# Outline

# Two different approaches

1. Count-based models

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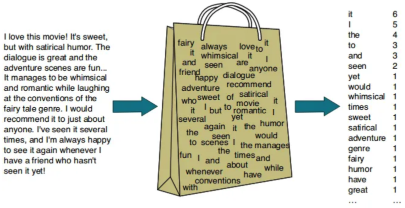
2. Neural network–based models

# Count-based Models

1. Start with a Bag-of-Words (BoW) representation

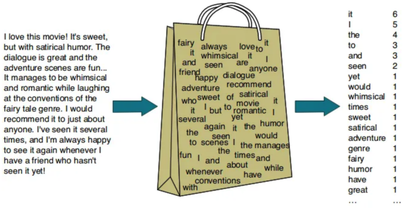
# Bag of Words




(source: `https://nachi-keta.medium.com/nlp-explain-bag-of-words-3b9fc4f211e8`)

- Bag-of-Words assumption: Context words are treated as unordered.

# Bag of Words

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- Bag-of-Words assumption: Context words are treated as unordered.
- In other words, the position of a context word relative to the target is ignored.

## Count-based Models

2. Extend to a co-occurrence matrix: count how often words appear together in a context window

**Example sentences:**

- I like apples.

**Example sentences:**

- I like apples.
- You like bananas.

**Example sentences:**

- I like apples.
- You like bananas.
- They eat bananas.

**Example sentences:**

- I like apples.
- You like bananas.
- They eat bananas.
- We enjoy apples.

**Example sentences:**

- I like apples.
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| | I | you | we | they | like | eat | enjoy | apples | bananas | fruit |
|---|---|---|---|---|---|---|---|---|---|---|
| I | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 |
| you | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 |
| we | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 |
| they | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 |
| like | 1 | 1 | 0 | 1 | 0 | 0 | 0 | 1 | 1 | 1 |
| eat | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 |
| enjoy | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 |
| apples | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 0 |
| bananas | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 |
| fruit | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 |

Co-occurrence Matrix (window size $= 1$)

# Count-based Models

3. Apply Singular Value Decomposition (SVD) to reduce dimensions (i.e., a way of breaking a big matrix into a smaller pieces)

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  - Adding new words requires recomputing the entire matrix and SVD

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- 2013: Word2Vec (Skip-gram, CBOW)
- 2014–2015: GloVe, fastText
- 2018– : Contextual embeddings (ELMo, BERT, GPT)

# Today's presentations

- Emily: Mikolov et al. (2013). *Efficient Estimation of Word Representations in Vector Space.* (Word2Vec)

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- Emily: Mikolov et al. (2013). *Efficient Estimation of Word Representations in Vector Space.* (Word2Vec)
- Sindhu: Pennington et al. (2014). *GloVe: Global Vectors for Word Representation* (GloVe)

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- Idea:
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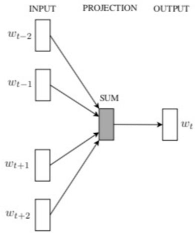
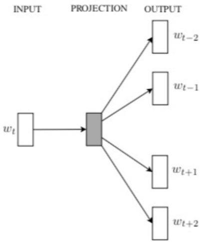
  - Every word in a fixed vocabulary is represented by a **vector**
  - Go through each position $t$ in the text, which has a center word $c$ and context word $o$ (window, n-gram)
  - Use the similarity of the word vectors for $c$ and $o$ to **calculate the probability** of $o$ given $c$ (or vice versa) $\leftarrow$ Neural network-based model

# Word2vec: Two models




Continuous Bag of Words (CBOW):
predicting the center words using
the context words ($P(w_t|w_{t-2}, w_{t-1}, w_{t+1}, w_{t+2})$)




Skip-grams (SG):
predicting the context words using
the center word ($P(w_{t+i}|w_t), i \in \{-2, -1, 1, 2\}$)

Focus on **Skip-gram**.

# Word2Vec: Skip-grams (*window size* = 1)

- "king brave man"
- "queen beautiful woman"

| **word** | **neighbor** |
|---|---|
| king | brave |
| brave | king |
| brave | man |
| man | brave |
| queen | beautiful |
| beautiful | queen |
| beautiful | woman |
| woman | beautiful |

# Word2Vec: Skip-grams (*window size* = 2)

- "king brave man"
- "queen beautiful woman"

| **word** | **neighbor** |
|---|---|
| king | brave |
| king | man |
| brave | man |
| brave | king |
| man | king |
| man | brave |
| queen | beautiful |
| queen | woman |
| beautiful | queen |
| beautiful | woman |
| woman | queen |
| woman | beautiful |

# Word2Vec: Skip-grams (window size = 2)

| word | one-hot encoding | neighbor | one-hot encoding |
|---|---|---|---|
| king | [1, 0, 0, 0, 0, 0] | brave | [0, 1, 0, 0, 0, 0] |
| king | [1, 0, 0, 0, 0, 0] | man | [0, 0, 1, 0, 0, 0] |
| brave | [0, 1, 0, 0, 0, 0] | man | [0, 0, 1, 0, 0, 0] |
| brave | [0, 1, 0, 0, 0, 0] | king | [1, 0, 0, 0, 0, 0] |
| man | [0, 0, 1, 0, 0, 0] | king | [1, 0, 0, 0, 0, 0] |
| man | [0, 0, 1, 0, 0, 0] | brave | [0, 1, 0, 0, 0, 0] |
| queen | [0, 0, 0, 1, 0, 0] | beautiful | [0, 0, 0, 0, 1, 0] |
| queen | [0, 0, 0, 1, 0, 0] | woman | [0, 0, 0, 0, 0, 1] |
| beautiful | [0, 0, 0, 0, 1, 0] | queen | [0, 0, 0, 1, 0, 0] |
| beautiful | [0, 0, 0, 0, 1, 0] | woman | [0, 0, 0, 0, 0, 1] |
| woman | [0, 0, 0, 0, 0, 1] | queen | [0, 0, 0, 1, 0, 0] |
| woman | [0, 0, 0, 0, 0, 1] | beautiful | [0, 0, 0, 0, 1, 0] |

# Word2Vec: Input and output

| input |
|---|
| [1, 0, 0, 0, 0, 0] |
| [1, 0, 0, 0, 0, 0] |
| [0, 1, 0, 0, 0, 0] |
| [0, 1, 0, 0, 0, 0] |
| [0, 0, 1, 0, 0, 0] |
| [0, 0, 1, 0, 0, 0] |
| [0, 0, 0, 1, 0, 0] |
| [0, 0, 0, 1, 0, 0] |
| [0, 0, 0, 0, 1, 0] |
| [0, 0, 0, 0, 1, 0] |
| [0, 0, 0, 0, 0, 1] |
| [0, 0, 0, 0, 0, 1] |

| output |
|---|
| [0, 1, 0, 0, 0, 0] |
| [0, 0, 1, 0, 0, 0] |
| [0, 0, 1, 0, 0, 0] |
| [1, 0, 0, 0, 0, 0] |
| [1, 0, 0, 0, 0, 0] |
| [0, 1, 0, 0, 0, 0] |
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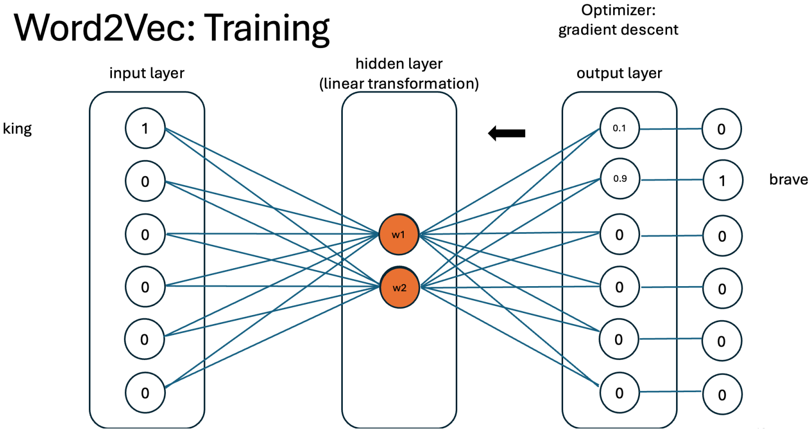
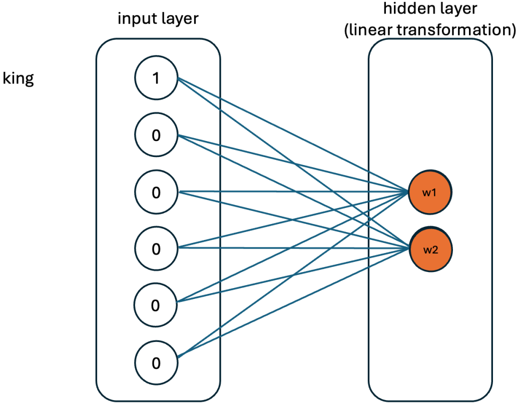
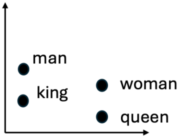
| [0, 0, 0, 0, 1, 0] |

# Word2Vec: Training






| word | embedding |
|---|---|
| king | [1, 1] |
| brave | [1, 2] |
| man | [1, 3] |
| queen | [5, 1] |
| beautiful | [5, 2] |
| woman | [5, 3] |



# 1. One-hot and embedding lookup

- Each word in the vocabulary is represented as a **dense vector**.

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- Each word in the vocabulary is represented as a **dense vector**.
- All these word vectors are stored in a single matrix:

**Embedding matrix** $E \in \mathbb{R}^{V \times d}$

# 2. Predicting context words

- Take the center word's embedding

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- Compare it with each candidate context word's output vector

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- Compare it with each candidate context word's output vector
- Compute a **dot product** as a similarity score (see Appendix)

# 3. From similarity scores to probabilities

- After retrieving the center word and a context word's vectors, we compute their **dot product**:

$$\text{score} = \vec{v}_c \cdot \vec{u}_w$$

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$$\sigma(\text{score}) = \frac{1}{1 + e^{-\text{score}}}$$

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$$\text{score} = \vec{v}_c \cdot \vec{u}_w$$

- To interpret this score as a probability, we apply the **sigmoid function**:

$$\sigma(\text{score}) = \frac{1}{1 + e^{-\text{score}}}$$

- The output is a number between 0 and 1 — representing how likely this word is to appear in the context.

## 4. Compute loss

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- The model is rewarded when:
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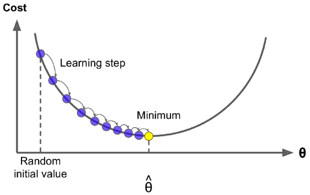
  - It assigns low probability to negative (random) words
- The model adjusts vectors to maximize the probability of real words and minimize that of negatives

# 5. Update word vectors

- Optimizer updates parameters based on gradients



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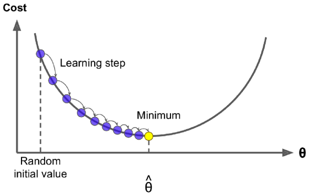


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# 5. Update word vectors

- Optimizer updates parameters based on gradients
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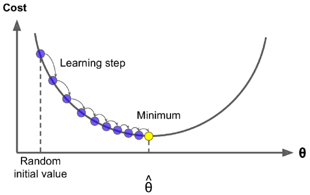
  - The center word's vector



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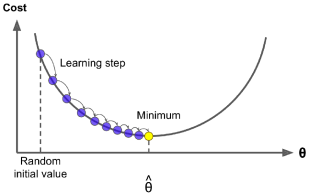

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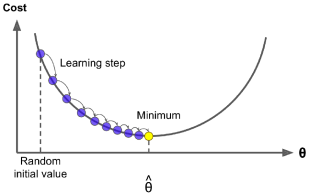

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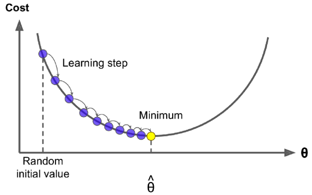
  - The negative samples' vectors
- Over time, words with similar contexts move closer



We'll discuss more about the neural network next week.

# Outline

# From mini survey

- Q. Where to go to request an official doc for late assignment?

# From mini survey

- Q. Where to go to request an official doc for late assignment?
- A: Please email me first.

# Thursday

- **Thursday**: Lab 2 — Word2Vec and GloVe; Presenter: Leona

# Paper presentation

Please upload your slides on mycourses $\rightarrow$ assignment $\rightarrow$ presentation - BEFORE your presentation.

# Outline

## Dot product as similarity score

- **Algebraic definition:** For two vectors $a = (a_1, \ldots, a_n)$ and $b = (b_1, \ldots, b_n)$,

$$a \cdot b = \sum_{i=1}^{n} a_i b_i$$

(multiply each coordinate and add them up)

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(multiply each coordinate and add them up)

- **Geometric interpretation:** The same dot product can also be written as

$$a \cdot b = \|a\| \, \|b\| \cos \theta$$

where $\theta$ is the angle between $a$ and $b$. Larger values $\Rightarrow$ vectors point in a similar direction (more related).

- **In Word2Vec:**

$$s(w|c) = v_c \cdot u_w = \sum_{i=1}^{d} v_{c,i}\, u_{w,i}$$

where $v_c$ is the center word vector, $u_w$ is a candidate context vector.

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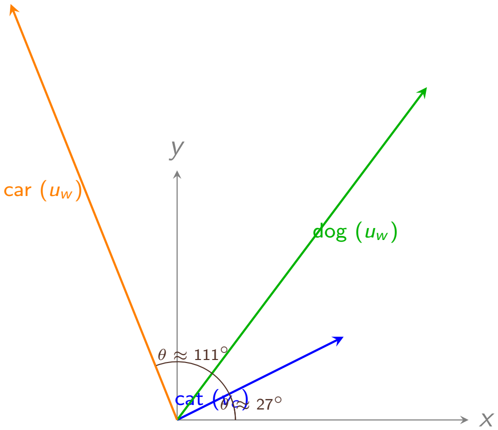
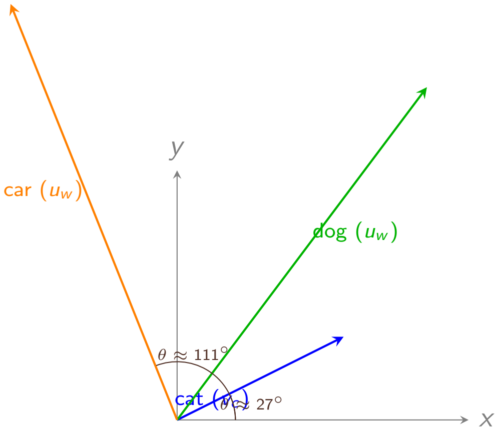
- **Comparison:** $u_w = [-2, 5]$ ("car")

$$v_c \cdot u_w = (2 \times -2) + (1 \times 5) = 1$$




- $v_c = [2,1]$ ("cat"), $u_w = [3,4]$ ("dog") $\quad v_c \cdot u_w = 10 \quad \Rightarrow$ large positive (similar direction).




- $v_c = [2, 1]$ ("cat"), $u_w = [3, 4]$ ("dog") $\quad v_c \cdot u_w = 10 \quad \Rightarrow$ large positive (similar direction).
- $v_c = [2, 1]$ ("cat"), $u_w = [-2, 5]$ ("car") $\quad v_c \cdot u_w = 1 \quad \Rightarrow$ small (weak relation).