1. What is Word Embedding?

Definition (Technical):

Word embedding is a method of representing words as **numerical vectors** in a continuous vector space, where words with similar meanings are located close to each other.

Instead of representing words as **one-hot vectors** (sparse and high-dimensional), embeddings give us **dense**, **low-dimensional vectors** that capture **semantic meaning**.

2. Why We Need Word Embeddings

Before embeddings, the common method was **one-hot encoding**:

- If you have a vocabulary of 10,000 words, each word is represented as a **10,000-dimensional vector** with only one "1" and the rest "0"s.
- Problems:
 - 1. No semantic meaning: "Cat" and "Dog" are as far apart as "Cat" and "Car".
 - 2. High dimensionality: Inefficient storage and computation.
 - 3. **Sparse representation**: Most values are zero → waste of space.

Word embeddings solve this by:

- Compressing to smaller dimensions (e.g., 300D instead of 10,000D).
- Making similar words numerically close in vector space.
- Allowing models to learn meaning from context.

3. Example of Word Embedding

Let's say we train an embedding model (like Word2Vec, GloVe, or FastText) and get these 3D representations (for illustration; real ones are usually 100–300D):

Word Embedding Vector

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Cat [0.21, 0.58, 0.35]
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Dog [0.20, 0.60, 0.33]

Car [0.91, 0.11, 0.56]

Observation:

- Distance between **Cat** and **Dog** is small → meaning is similar (both are animals).
- Distance between Cat and Car is large → meaning is unrelated.

Cool property:

Some embeddings capture analogies, e.g.:

$$Vector("King") - Vector("Man") + Vector("Woman") \approx Vector("Queen")$$

4. Why This Helps Models

When models receive embeddings instead of raw words:

- They can **understand relationships** like synonyms, analogies, and categories.
- They require less data to learn meaningful patterns.
- They perform better in **NLP tasks** like sentiment analysis, translation, and question answering.

In short:

- Word Embedding = compact, meaningful numerical representation of words.
- Why = reduces dimensions, captures meaning, improves learning efficiency.
- **Example** = "Cat" and "Dog" vectors are close; "Cat" and "Car" are far apart.