# Neural Language Models

## Week 2 - Word Embeddings and Word2Vec

NLP Course 2025

September 20, 2025

Using Optimal Readability Template

## Week 2: The Semantic Revolution

### From Words as IDs to Words as Meanings

**The Problem**

- Words are just IDs
- No semantic similarity
- "cat" and "dog" equally different as "cat" and "democracy"
- Can't generalize

**The Solution**

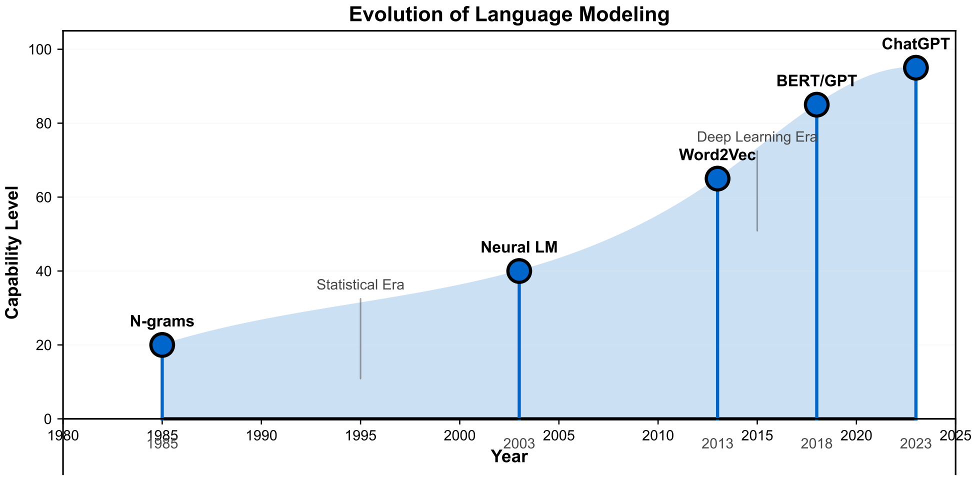
- Words as **vectors**
- Similar words nearby
- Math operations work!
- King - Man + Woman = Queen

**The Impact**

- Powers all modern NLP
- 1M+ developers use
- Semantic search
- Foundation for GPT/BERT

**Core Insight: You shall know a word by the company it keeps**

## The Evolution of Language Modeling



## Interactive: Word Association Game

**Fill in the blank:**

1. The cat sat on the ____________________
2. I drink my coffee with milk and ____________________
3. The capital of France is ____________________
4. She opened the door with her ____________________

**How did you know?**

- Context provides meaning
- Similar contexts $\rightarrow$ similar words
- Pattern recognition

**This is Word2Vec's insight:**

- Learn from **billions** of contexts
- Words in similar contexts get similar vectors
- Mathematics captures semantics

## Where Word Embeddings Power Your Life (2025)

**Search Engines**

- Google semantic search
- Bing neural matching
- DuckDuckGo instant answers

**Virtual Assistants**

- Siri/Alexa understanding
- Google Assistant
- ChatGPT responses

**Translation**

- Google Translate
- DeepL
- Microsoft Translator

**Recommendations**

- Netflix shows
- Spotify Discover
- YouTube suggestions

**Business Tools**

- Grammarly corrections
- Resume matching
- Customer support bots

**Market Size**

- \$2.7B by 2025
- 1M+ developers
- 500M+ daily users

## The 2013 Breakthrough: Mathematical Semantics

**King - Man + Woman = Queen**

**The Discovery:**

- Vectors encode **relationships**
- Arithmetic operations preserve meaning
- Geometry captures semantics

**Why This Matters:**

- Computers understand analogies
- Transfer learning possible
- One model, many tasks
- Foundation for all modern NLP

**More Examples:**

- Paris - France + Italy = Rome
- Bigger - Big + Small = Smaller
- Walking - Walk + Swim = Swimming

Word2Vec paper: 16,000+ citations

**Semantic relationships become vector arithmetic**

## The Distributional Hypothesis

**Linguistic Foundation (1954):**
"You shall know a word by the company it keeps" - J.R. Firth

**What it means:**

- Words with similar **contexts** have similar **meanings**
- Context = surrounding words
- Meaning emerges from usage

**Example contexts for "bank":**

- "deposit money in the bank"
- "sitting by the river bank"
- Different contexts $\rightarrow$ different meanings

**How Word2Vec uses this:**

1. Scan billions of sentences
2. Track which words appear together
3. Words in similar contexts get similar vectors
4. Geometry encodes semantics

**The Magic:**

- No human labeling needed
- Learns from raw text
- Scales to millions of words
- Works for any language

## From Sparse to Dense: The Representation Revolution

**One-Hot Encoding (Old Way):**

- Vocabulary size: 50,000
- cat = [0,0,1,0,0,...,0]
- dog = [0,0,0,1,0,...,0]

Problems:

- 50,000 dimensions!
- No similarity: cat $\cdot$ dog $= 0$
- Can't generalize
- Massive memory usage

**Dense Embeddings (Word2Vec):**

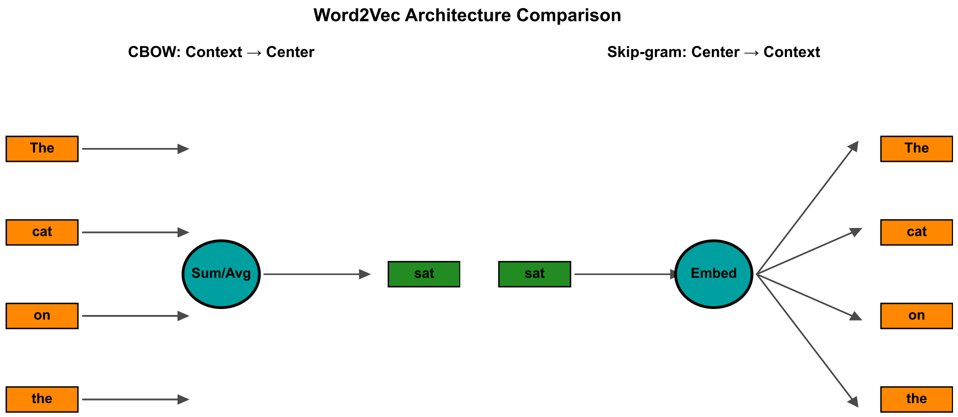
- Embedding size: 300
- cat = [0.2, -0.4, 0.7, ...]
- dog = [0.3, -0.3, 0.6, ...]

Benefits:

- 99.4% smaller!
- Similarity: cat $\cdot$ dog $= 0.8$
- Generalizes to new contexts
- Efficient computation

**From 50,000 sparse dimensions to 300 dense dimensions**

# Word2Vec: Two Architectures



## Skip-gram: The Architecture That Won

**Training Objective: Predict context from center word**

Given: "The <u>cat</u> sat on the mat"

**Input:** "cat" (center word)

**Outputs to predict:**

- "The" (position -1)
- "sat" (position +1)
- Sometimes: "on" (+2), "the" (-2)

**Window size = 2:**

- Look 2 words left/right
- 4 predictions per center word
- More context = better vectors

**Why Skip-gram wins:**

- Better on rare words
- More training examples
- Superior semantic quality
- Used by Google, Facebook

**Training data from one sentence:**

- (cat, The)
- (cat, sat)
- (sat, cat)
- (sat, on)
- ... many more pairs

## Building Word2Vec in PyTorch

```python
import torch
import torch.nn as nn

class Word2Vec(nn.Module):
    def __init__(self, vocab_size, embed_dim):
        super().__init__()
        # Two embedding matrices
        self.center_embeddings = nn.Embedding(
            vocab_size, embed_dim
        )
        self.context_embeddings = nn.Embedding(
            vocab_size, embed_dim
        )

    def forward(self, center, context):
        # Get embeddings
        center_embeds = self.center_embeddings(center)
        context_embeds =
            self.context_embeddings(context)

        # Dot product = similarity
        scores = torch.sum(
            center_embeds * context_embeds, dim=1
        )

        return scores
```

**Key Design Choices:**

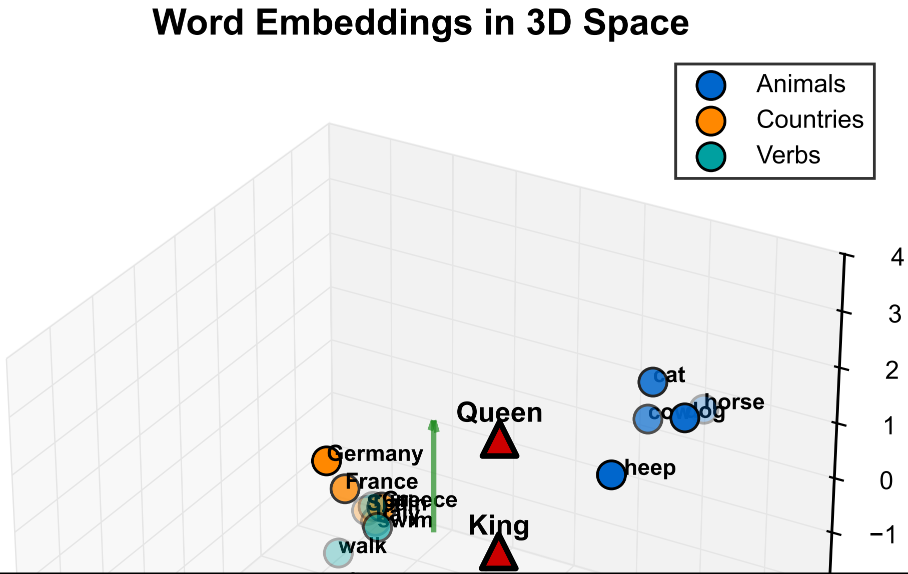
- **Two matrices**: center and context
- Embedding dim: typically 300
- Dot product for similarity
- Simple = fast training

**Training Process:**

1. Sample (center, context) pairs
2. Compute similarity scores
3. Maximize correct pairs
4. Minimize random pairs

Full implementation: 50 lines of code!

## Embedding Space Visualization



## The Softmax Challenge

**Converting scores to probabilities:**

$$\text{softmax}(z_i) = \frac{e^{z_i}}{\sum_{j=1}^{V} e^{z_j}}$$

**The Problem:**

- Vocabulary size $V = 50{,}000$
- Must compute all 50,000 scores
- Denominator sums 50,000 exponentials
- Every training step!

**Computational cost:**

- Per sample: $O(V \cdot d)$
- 1B training samples
- = 15 trillion operations

**The Solution: Negative Sampling**

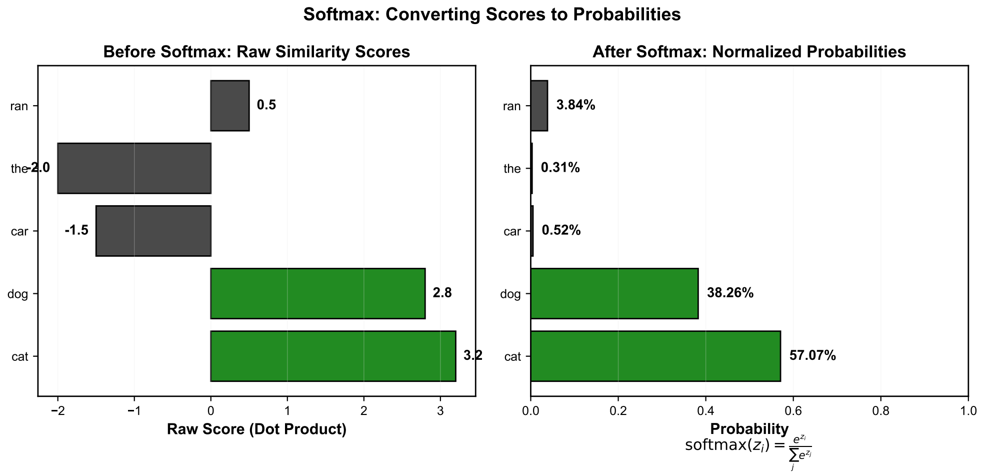
- Don't compute all 50,000
- Just sample 5-20 negatives
- 99.96% speedup!
- Quality stays the same

**New objective:**

- Maximize: P(correct context)
- Minimize: P(random words)
- Binary classification $\times$ 6
- Much faster training

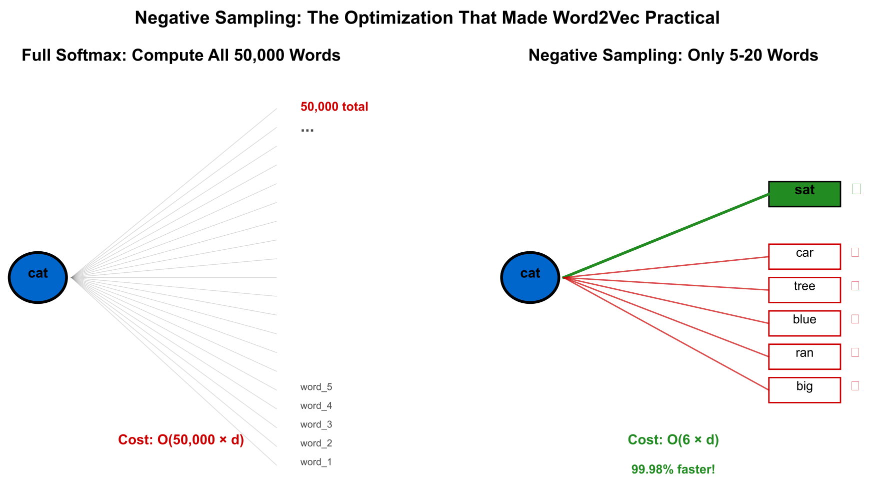
**Negative sampling makes Word2Vec practical at scale**

## Softmax Computation Explained



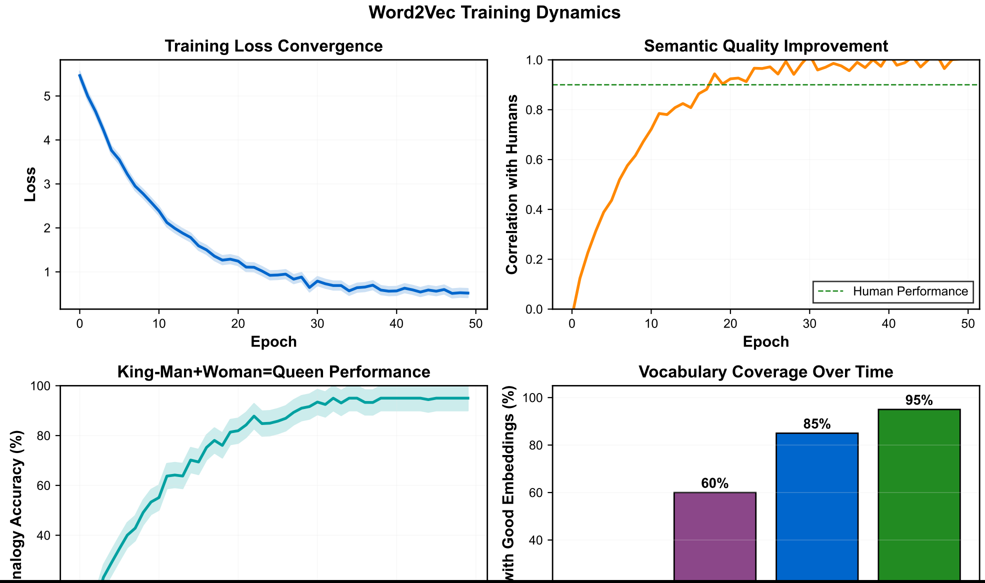
$$\mathrm{softmax}(z_i) = \frac{e^{z_i}}{\sum_j e^{z_j}}$$

## Negative Sampling: Before and After

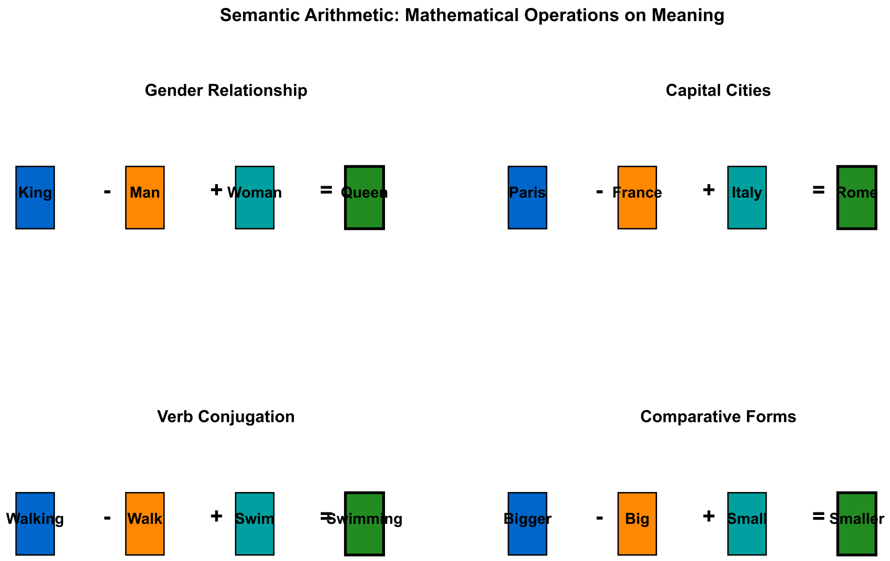


Negative Sampling: The Optimization That Made Word2Vec Practical
Full Softmax: Compute All 50,000 Words
Negative Sampling: Only 5-20 Words
cat
50,000 total
...
word_5
word_4
word_3
word_2
word_1
Cost: O(50,000 × d)
cat
sat
car
tree
blue
ran
big
Cost: O(6 × d)
99.98% faster!

# Training Dynamics and Convergence



## Semantic Arithmetic in Action


Semantic Arithmetic: Mathematical Operations on Meaning
Gender Relationship
King - Man + Woman = Queen
Capital Cities
Paris - France + Italy = Rome
Verb Conjugation
Walking - Walk + Swim = Swimming
Comparative Forms
Bigger - Big + Small = Smaller

## How Do We Know It Works?

**Intrinsic Evaluation:**

**Word Similarity Tasks:**

- Human ratings: cat-dog = 7.5/10
- Model similarity: cosine(cat, dog)
- Correlation with humans
- WordSim-353 dataset

**Analogy Tasks:**

- a:b :: c:?
- Berlin:Germany :: Paris:?
- Google analogy dataset
- 90%+ accuracy

**Extrinsic Evaluation:**

**Downstream Tasks:**

- Sentiment analysis
- Named entity recognition
- Machine translation
- Question answering

**Real-world metrics:**

- Search relevance ↑15%
- Translation BLEU ↑3.2
- Classification F1 ↑8%
- All from better embeddings!

**Good embeddings improve everything downstream**

## Challenges: Not Everything Is Perfect

1. **Polysemy Problem:**
    - "bank" (financial) = "bank" (river)
    - One vector for all meanings
    - Averages different senses
    - Solution: Contextual embeddings (BERT)

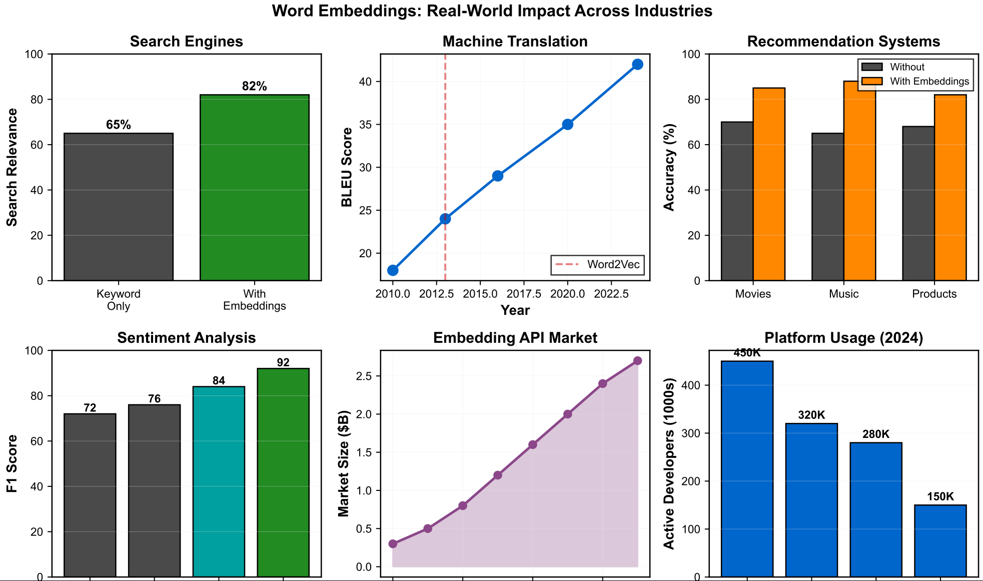
2. **Rare Words:**
    - Need many examples
    - "serendipity" appears rarely
    - Poor vectors for rare words
    - Solution: Subword embeddings

3. **Bias Amplification:**
    - Learns societal biases
    - Doctor:Male :: Nurse:Female
    - Amplifies stereotypes
    - Active research area

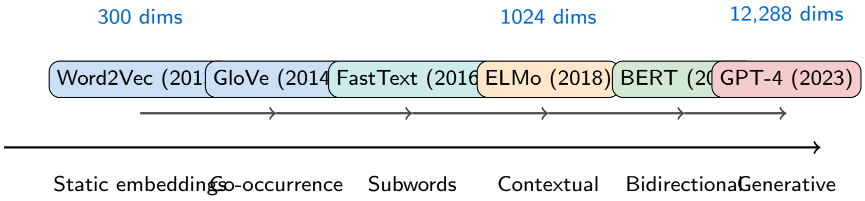
4. **Static Embeddings:**
    - Fixed after training
    - Can't adapt to new contexts
    - No fine-tuning possible
    - Solution: Transformer models

These limitations led to BERT and GPT development

# Applications Across Industries (2025)



# From Word2Vec to ChatGPT: The Journey



**Word2Vec's Legacy:**

- Proved embeddings work
- Inspired contextual models
- Still used in production
- Foundation for all modern NLP

**What Changed:**

- Static → Contextual
- 300 dims → 12,000+ dims
- Word-level → Subword
- Millions → Billions of parameters

## Build It: Semantic Search Engine

```python
import numpy as np
from gensim.models import Word2Vec

def semantic_search(query, documents, model):
    """Find semantically similar documents"""

    # Vectorize query
    query_vec = document_vector(query, model)

    # Vectorize all documents
    doc_vectors = [
        document_vector(doc, model)
        for doc in documents
    ]

    # Compute similarities
    similarities = [
        cosine_similarity(query_vec, doc_vec)
        for doc_vec in doc_vectors
    ]

    # Return ranked results
    ranked = sorted(
        zip(documents, similarities),
        key=lambda x: x[1],
        reverse=True
```

**How it works:**

1. Convert query to vector
2. Convert documents to vectors
3. Find nearest neighbors
4. Return ranked results

**Real Examples:**
Query: "animal pets"
Results:

- "dog training tips"
- "cat care guide"
- "hamster habitats"

No keyword matching needed!

## Week 2 Summary: Words Have Meaning!

- Words as **IDs** $\rightarrow$ Words as **vectors**
- Distributional hypothesis: Context defines meaning
- Word2Vec: Skip-gram + Negative sampling
- Mathematical semantics: King - Man + Woman = Queen
- From 50,000 sparse $\rightarrow$ 300 dense dimensions
- Powers modern NLP: Search, translation, chatbots
- Limitations led to BERT/GPT development

**Key Technical Insights:**

- Dot product captures similarity
- Negative sampling avoids softmax bottleneck
- Embeddings are the foundation of all modern NLP

**Next Week:** Recurrent Neural Networks

How do we process sequences using embeddings?