# Neural Language Models

## Week 2: Word Embeddings and Word2Vec

NLP Course 2025

Professional Template Edition

September 29, 2025

# Week 2: Journey Through Word Embeddings

**Learning Path:** From discrete word IDs to continuous semantic vectors. Master how neural networks learn word meaning through context, leading to the Word2Vec revolution that powers modern NLP.

# Part 1: Introduction & Motivation

# Interactive: Word Association Game

**Fill in the blank - What word naturally comes next?**

1. The cat sat on the ____________________

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2. I drink my coffee with milk and ____________________

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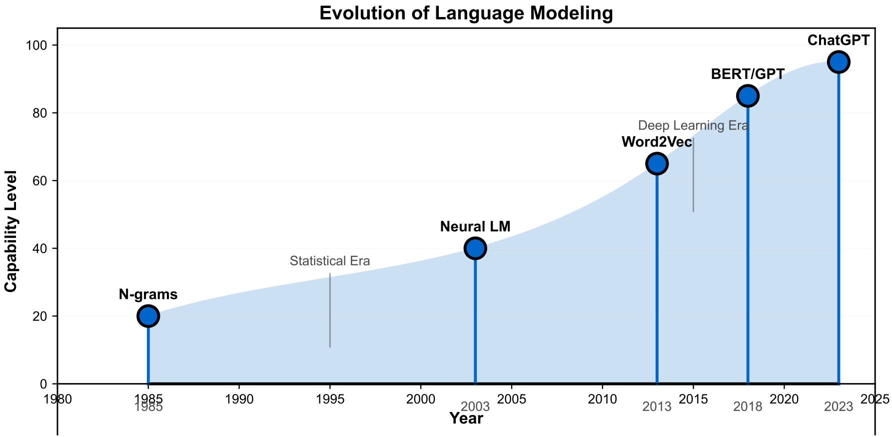
4. She was happy but also felt ________________ $\rightarrow$ sad, anxious, confused (emotions)

**Humans predict words using semantic understanding - how can computers learn this?**

# The Evolution of Language Modeling




**Four Major Eras in Next-Word Prediction:**

- **1980s-2000s:** Statistical N-grams - Count and predict
- **2003-2013:** Neural Language Models - First neural approaches

# The Fundamental Problem

**Traditional Approach: One-Hot Encoding**

- Words as discrete IDs
- Vocabulary size: 10,000 words
- "cat" = [0,0,1,0,...,0] (position 3)
- "dog" = [0,0,0,0,1,...,0] (position 5)

**Problems:**

- No notion of similarity
- distance(cat, dog) = distance(cat, democracy)
- Can't generalize knowledge
- Huge, sparse vectors

**Solution: Dense Embeddings**

- Words as dense vectors
- Dimension: 100-300 (not 10,000!)
- "cat" = [0.2, -0.4, 0.7, ...]
- "dog" = [0.3, -0.3, 0.8, ...]

**Benefits:**

- Similar words have similar vectors
- distance(cat, dog) ¡ distance(cat, democracy)
- Knowledge transfers between similar words
- Compact, meaningful representation

**Key Insight: Learn representations where geometric distance = semantic distance**

# Real-World Impact

**Search Engines**

- Semantic search
- Query understanding
- “car” finds “automobile”
- Intent matching

Used by:

- Google Search
- Bing
- DuckDuckGo

**Recommendations**

- Content similarity
- User preferences
- Cross-lingual matching
- Cold-start solutions

Used by:

- Netflix
- Spotify
- Amazon

**Language AI**

- Machine translation
- Sentiment analysis
- Chatbots
- Foundation for LLMs

Used by:

- ChatGPT
- Google Translate
- Grammarly

**Market Impact:** Word embeddings power $100B+ in NLP applications worldwide

**Word2Vec papers cited 50,000+ times - one of the most influential ML innovations**

# Part 2: Core Concepts

# The Distributional Hypothesis

"You shall know a word by the company it keeps"

*- J.R. Firth (1957)*

**Example Context Windows:**

- The **cat** sat on the mat
- The **dog** sat on the floor
- A **cat** chased the mouse
- A **dog** chased the ball

Shared contexts:

- Both appear after "The" and "A"
- Both appear before "sat", "chased"
- Both are subjects of similar actions

**Mathematical Formulation:**
Context window of size 2:

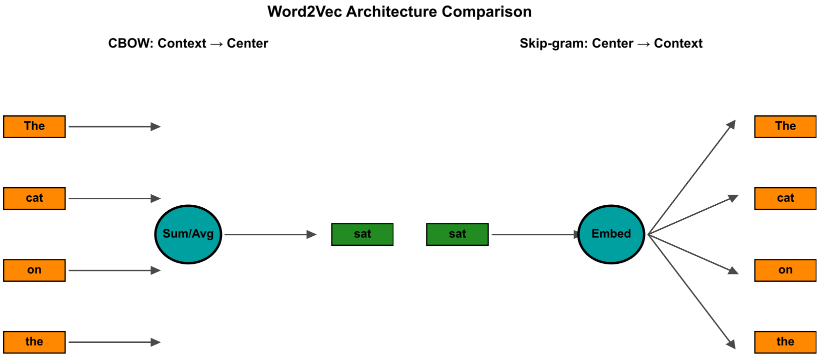
$$\text{context}(\text{cat}) = \{\text{The, sat, on, the}\}$$
$$\text{context}(\text{dog}) = \{\text{The, sat, on, the}\}$$

**Key Insight:**

- Similar contexts $\Rightarrow$ Similar meanings
- Learn vectors to predict context
- Vectors capture semantic similarity

**This simple idea - words with similar contexts have similar meanings - drives all embeddings**

# Word2Vec: Two Revolutionary Architectures




**CBOW (Continuous Bag-of-Words)**

- Predict center word from context
- Input: [The, cat, on, the]

**Skip-gram**

- Predict context from center word
- Input: sat

# The Mathematics of Word2Vec

**Skip-gram Objective Function:**

Maximize the probability of context words given center word:

$$J(\theta) = \frac{1}{T} \sum_{t=1}^{T} \sum_{-c \leq j \leq c, j \neq 0} \log P(w_{t+j} \mid w_t)$$

**Probability Calculation using Softmax:**

$$P(w_O \mid w_I) = \frac{\exp(v_{w_O}^T \cdot v_{w_I})}{\sum_{w=1}^{V} \exp(v_w^T \cdot v_{w_I})}$$

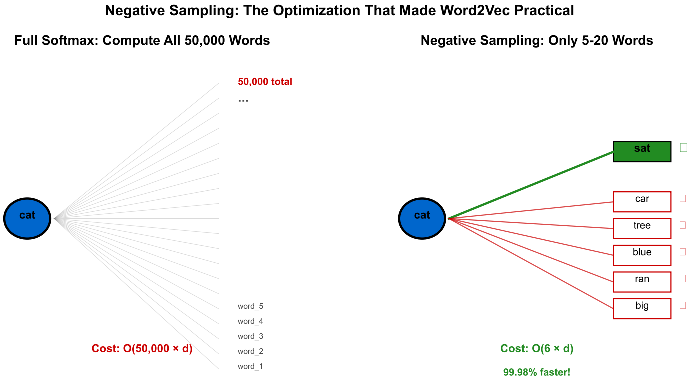
Where:

- $v_{w_I}$: Input vector for center word
- $v_{w_O}$: Output vector for context word
- $V$: Vocabulary size
- $c$: Context window size

**Problem:** Denominator sums over entire vocabulary (expensive!)

**Computing softmax over 50,000 words for every training example is computationally prohibitive**

# Negative Sampling: Making Training Feasible




**Convert to Binary Classification:**

Instead of softmax over all words:

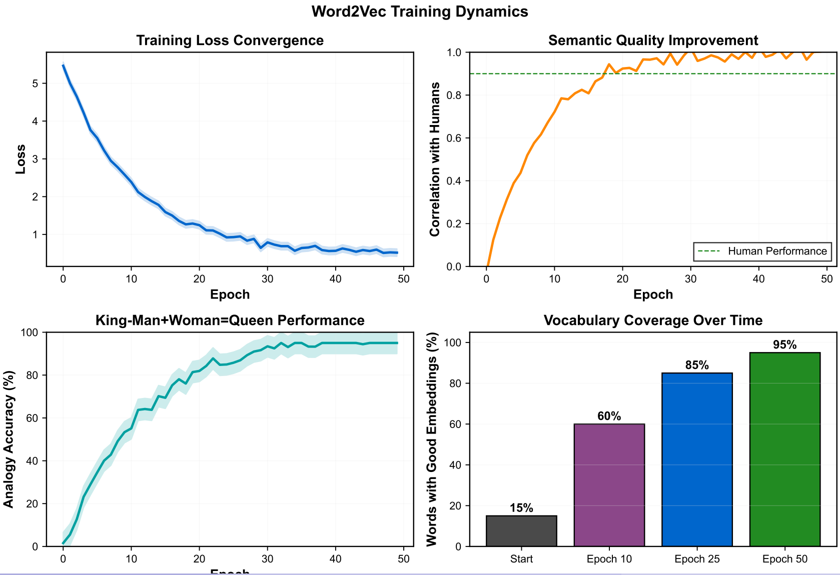
- Positive sample: (cat, sat) $\rightarrow$ 1
- Negative samples:
  - (cat, democracy) $\rightarrow$ 0

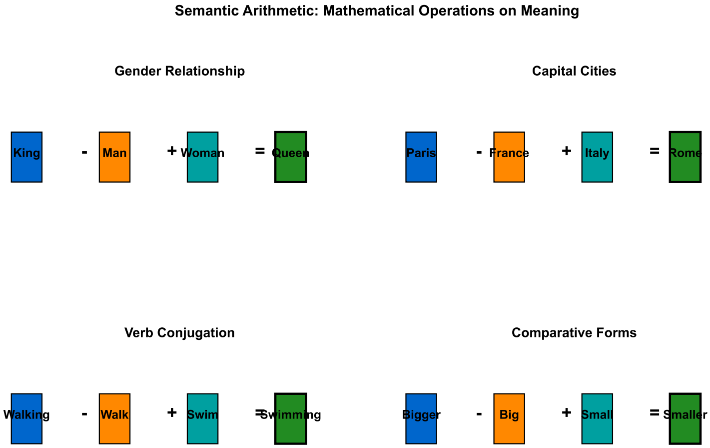
**New Objective:**

$$\log \sigma(v_{w_O}^T \cdot v_{w_I}) + \sum_k \log \sigma(-v_{w_k}^T \cdot v_{w_I})$$

# Part 3: Training & Solutions

# Training Dynamics: How Embeddings Evolve




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

# Evaluating Word Embeddings

**Intrinsic Evaluation**

- Word similarity tasks
- Analogy completion
- Clustering quality

**Benchmarks:**

- WordSim-353
- Google Analogy Test
- SimLex-999

**Metrics:**

- Spearman correlation
- Accuracy@1, @5
- Silhouette score

**Extrinsic Evaluation**

- Downstream task performance
- NER improvement
- Sentiment accuracy

**Tasks:**

- Text classification
- Machine translation
- Question answering

**Metrics:**

- F1 score improvement
- BLEU score gain
- Task-specific metrics

**Visualization**

- t-SNE projections
- PCA analysis
- Nearest neighbors

**Qualitative:**

- Semantic coherence
- Cluster separation
- Outlier detection

**Tools:**

- TensorBoard
- Embedding Projector
- Custom visualizations

**Best Practice:** Combine all three - numbers alone don't tell the whole story

**Good embeddings show 0.6+ correlation on similarity tasks and 3-5% improvement on downstream tasks**

# Limitations and Advanced Solutions

**Fundamental Limitations:**

- Out-of-vocabulary words
  $\rightarrow$ FastText with subword units
- Single vector per word
  $\rightarrow$ Contextual embeddings (ELMo, BERT)
- No word order information
  $\rightarrow$ Position encodings
- Bias in training data
  $\rightarrow$ Debiasing techniques
- Fixed after training
  $\rightarrow$ Fine-tunable embeddings

**Advanced Techniques:**

- **GloVe (2014):**
  Combines global statistics + local context
- **FastText (2016):**
  Character n-grams for OOV handling
- **ELMo (2018):**
  Context-dependent embeddings
- **BERT (2018):**
  Bidirectional contextual representations
- **GPT (2018+):**
  Autoregressive language modeling

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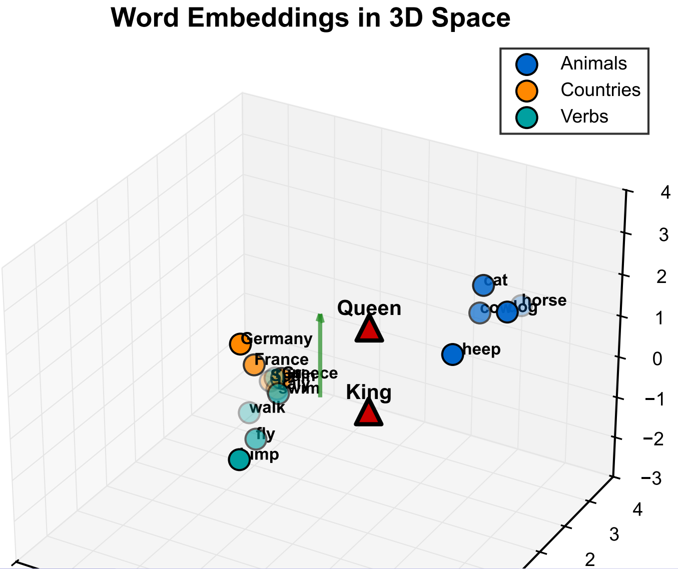
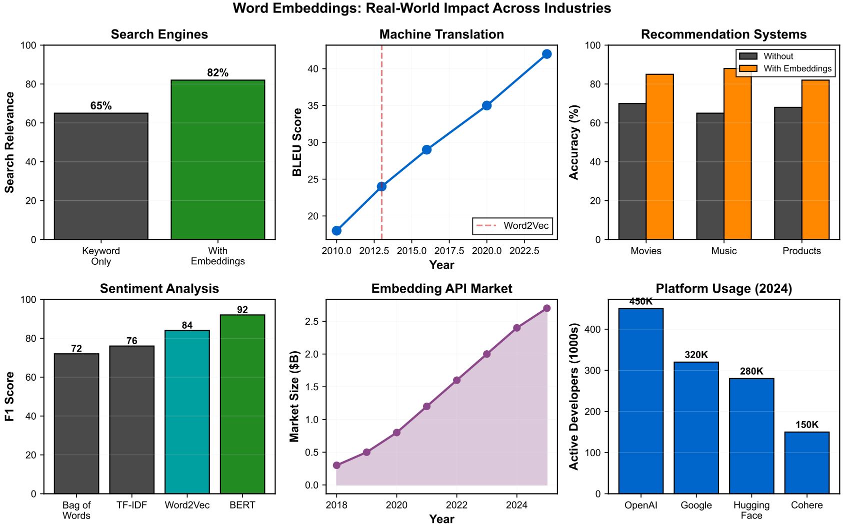
**Word2Vec's limitations led directly to the transformer revolution in NLP**

# Part 4: Applications & Future


Word Embeddings in 3D Space
Animals
Countries
Verbs
cat
horse
Queen
Germany
France
King
walk
fly
4
3
2
1
0
−1
−2
−3
4
3
2

# Modern Applications Dashboard

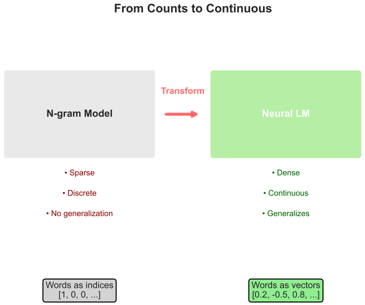


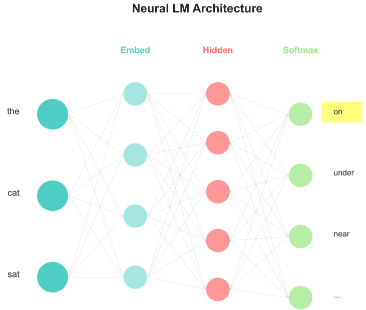
# Hands-On: Using Word2Vec in Practice

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

# Train Word2Vec model
sentences = [["the", "cat", "sat", "on", "the", "mat"],
             ["the", "dog", "sat", "on", "the", "floor"]]

model = Word2Vec(sentences, vector_size=100, window=5,
                 min_count=1, sg=1)  # sg=1 for skip-gram

# Get word vectors
cat_vector = model.wv['cat']
dog_vector = model.wv['dog']

# Compute similarity
similarity = model.wv.similarity('cat', 'dog')
print(f"Similarity(cat, dog) = {similarity:.3f}")

# Find similar words
similar_words = model.wv.most_similar('cat', topn=3)
print(f"Words similar to 'cat': {similar_words}")

# Word arithmetic
result = model.wv.most_similar(positive=['king', 'woman'],
                               negative=['man'], topn=1)
print(f"king - man + woman = {result[0][0]}")
```

**Gensim makes Word2Vec incredibly easy to use - training takes just minutes**

# From Word2Vec to Modern Transformers




**Word2Vec's Legacy:**

- Proved semantic learning possible
- Established embedding paradigm

**Modern Evolution:**

- BERT: Contextual embeddings
- GPT: Generative pre-training

# Summary: The Word Embedding Revolution

**What We Learned:**

**Key Concepts**

- Distributional hypothesis
- Dense vector representations
- Skip-gram vs CBOW
- Negative sampling optimization
- Semantic arithmetic

**Technical Skills**

- Training Word2Vec models
- Evaluating embedding quality
- Visualizing semantic spaces
- Applying to downstream tasks

**Practical Impact**

- Powers modern search engines
- Enables machine translation
- Foundation for ChatGPT/Claude
- $100B+ market impact

**Historical Significance**

- 50,000+ citations
- Revolutionized NLP (2013)
- Led to transformer era
- Still widely used today

**Core Insight: Words are not just symbols - they carry meaning in their**

# Quick Quiz: Test Your Understanding

**Answer these questions to check your understanding:**

1. What is the key insight of the distributional hypothesis?

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4. Why does "king - man + woman = queen" work?

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5. What's the main limitation of Word2Vec?

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4. Why does "king - man + woman = queen" work? → Relationships are encoded as vector directions
5. What's the main limitation of Word2Vec? → Single vector per word (no context dependence)

**If you can answer these, you understand the core of word embeddings!**

# Resources for Deep Dive

**Essential Papers**

- Mikolov et al. (2013a): Efficient Estimation
- Mikolov et al. (2013b): Distributed Representations
- Goldberg & Levy (2014): word2vec Explained
- Pennington et al. (2014): GloVe

**Implementations**

- Gensim (Python)
- TensorFlow Embeddings
- PyTorch nn.Embedding
- FastText library

**Datasets & Tools**

- Google News vectors
- GloVe pre-trained
- Embedding Projector
- Word2Vec demos

**Lab Session Preview:**

- Train Word2Vec on real corpus
- Explore semantic relationships
- Build a similarity search engine
- Visualize your own embeddings

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**Lab notebook: week02_word_embeddings_lab.ipynb**