Sentence Embeddings with Hugging Face

From Text to Numbers: Understanding Semantic Representations

BSc Level Tutorial

Natural Language Processing

Learning Objectives

By the end of this tutorial, you will be able to:

1. Understand what sentence embeddings are and why they are useful
2. Use the `sentence-transformers` library from Hugging Face
3. Generate embeddings with `SentenceTransformer('all-MiniLM-L6-v2')`
4. Calculate and interpret cosine similarity between sentences
5. Visualize high-dimensional embeddings using PCA and t-SNE
6. Apply embeddings to practical NLP tasks (search, clustering)

Prerequisite: Basic Python, basic linear algebra (vectors, dot products)

The Problem: How Do Computers Understand Text?

Traditional Approaches

- **Bag of Words**: Count word frequencies
- **One-Hot Encoding**: Binary vectors
- **TF-IDF**: Weighted term frequencies

Limitations:

- No semantic understanding
- Sparse, high-dimensional
- Cannot capture synonyms
- "King" and "Queen" are equally distant as "King" and "Table"

Modern Approach: Embeddings

- **Dense vectors**: Continuous representations
- **Semantic meaning**: Similar meanings → Similar vectors
- **Fixed dimension**: Same size for any text

Advantages:

- Captures semantic relationships
- Dense, efficient representations
- Similar words/sentences cluster together
- "King" and "Queen" are close, far from "Table"

Transition: From discrete symbols to continuous meaning vectors

From Text to Embeddings

"Team wins championship" → [0.12, -0.45, 0.78, ..., 0.34]

"President announces policy" $\xrightarrow{\text{SentenceTransformer}}$ [0.89, 0.23, -0.12, ..., -0.56]

"New AI breakthrough" → [-0.34, 0.67, 0.91, ..., 0.45]

384 dimensions per sentence

From Words to Sentences

Evolution of Embeddings:

1. **Word2Vec / GloVe** (2013-2014)
   - One vector per word
   - Problem: How to combine words into sentences?
2. **Sentence-BERT** (2019)
   - One vector per sentence
   - Built on BERT transformer architecture
   - Trained specifically for semantic similarity
3. **sentence-transformers** (Hugging Face library)
   - Easy-to-use Python library
   - Many pre-trained models
   - Production-ready

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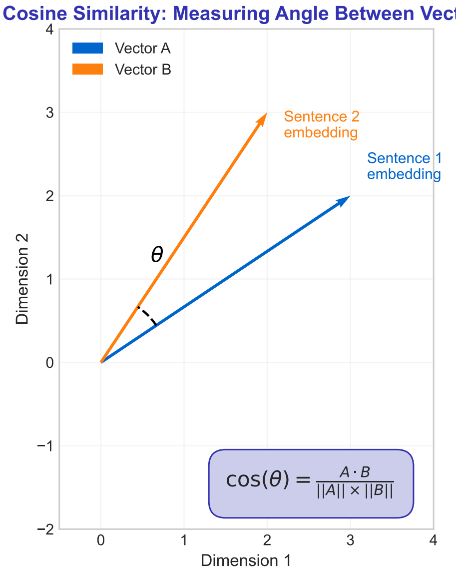
sentence-transformers: State-of-the-art made accessible


Cosine Similarity: Measuring Angle Between Vectors
Vector A
Vector B
Sentence 2 embedding
Sentence 1 embedding
θ
$\cos(\theta) = \frac{A \cdot B}{||A|| \times ||B||}$
Dimension 2
Dimension 1
4
3
2
1
0
−1
−2
0
1
2
3
4

Definition:

Introducing sentence-transformers

What is sentence-transformers?

- Python library built on Hugging Face Transformers
- Provides pre-trained models for semantic similarity
- Easy to use: Just 3 lines of code to get started
- Production-ready: Used in industry applications

Installation:

```
pip install sentence-transformers
```

Why use it?

- No training required (pre-trained models)
- Consistent API across 100+ models
- Well-documented and maintained
- Perfect for learning and prototyping

Documentation: sbert.net — Hugging Face: huggingface.co/sentence-transformers

The Model: all-MiniLM-L6-v2

Model Specifications

- **Architecture**: MiniLM (distilled BERT)
- **Embedding dimension**: 384
- **Model size**: 80 MB
- **Speed**: 500 sentences/sec (CPU)
- **Training**: 1B+ sentence pairs
- **Performance**: 82% Spearman correlation

Technical Details

- Distilled from larger BERT model
- 6 transformer layers
- Mean pooling strategy
- Trained on diverse text pairs

Why This Model?

- **Small & Fast**: Good for learning
- **High Quality**: State-of-the-art performance
- **Well-Documented**: Easy to understand
- **BSc-Appropriate**: Not overwhelming

Alternatives

- **Higher quality**: all-mpnet-base-v2 (768D)
- **Multilingual**: paraphrase-multilingual-*
- **Faster**: all-MiniLM-L3-v2 (smaller)
- **Domain-specific**: Fine-tune your own

Model card: huggingface.co/sentence-transformers/all-MiniLM-L6-v2

Code Example: Loading the Model

Step 1: Import the library

```python
from sentence_transformers import SentenceTransformer
```

Step 2: Load the pre-trained model

```python
# Load model (downloads ~80 MB on first run)
model = SentenceTransformer('all-MiniLM-L6-v2')

# Model is ready to use!
# No training, no configuration needed
```

That's it! The model is now ready to generate embeddings.

Note: First run downloads the model. Subsequent runs load from cache.

One line of code to load a state-of-the-art language model!

Code Example: Generating Embeddings

Step 3: Encode sentences

```python
# Your text data
headlines = [
    "President announces new climate policy",
    "Team wins championship after overtime",
    "New AI breakthrough announced at conference"
]

# Generate embeddings
embeddings = model.encode(headlines)

# Result: NumPy array of shape (3, 384)
print(embeddings.shape)  # (3, 384)
print(type(embeddings))  # <class 'numpy.ndarray'>
```

Each headline → 384 numbers capturing its meaning

Three lines of actual code: Import, Load, Encode. That's all!

Understanding the Output

What do the numbers mean?

```python
# First embedding (first 10 dimensions shown)
print(embeddings[0][:10])
```

Output:

```
[-0.008, 0.002, 0.055, -0.021, 0.046, -0.020, -0.087, -0.042, -0.003, 0.044]
```

Properties:

- **Normalized**: Length (norm) = 1.0
- **Dense**: All 384 dimensions have meaningful values
- **Fixed size**: Same dimensions regardless of sentence length
- **Meaningful**: Similar sentences have similar vectors

Each dimension captures some aspect of meaning - learned from training data

Our Dataset: 10,000 News Headlines

Dataset Statistics:

- **Total headlines**: 10,000
- **Categories**: 4 (Politics, Sports, Technology, Entertainment)
- **Per category**: 2,500 headlines (balanced)
- **Average length**: 7 words per headline

Embedding Generation:

- **Time**: 20 seconds on CPU
- **Output size**: $10{,}000 \times 384 = 3.84$ million numbers
- **File size**: 15 MB (as NumPy array)
- **Quality**: High semantic similarity within categories

Challenge: How do we visualize 384 dimensions?

Solution: Dimensionality reduction (PCA, t-SNE)

Dimensionality Reduction: The Visualization Challenge

Problem: We cannot visualize 384 dimensions directly

Solution: Reduce to 2 dimensions while preserving structure

PCA (Principal Component Analysis)

- **Linear** transformation
- Finds directions of maximum variance
- Fast and deterministic
- Good for global structure
- May miss non-linear patterns

Best for: Understanding overall distribution

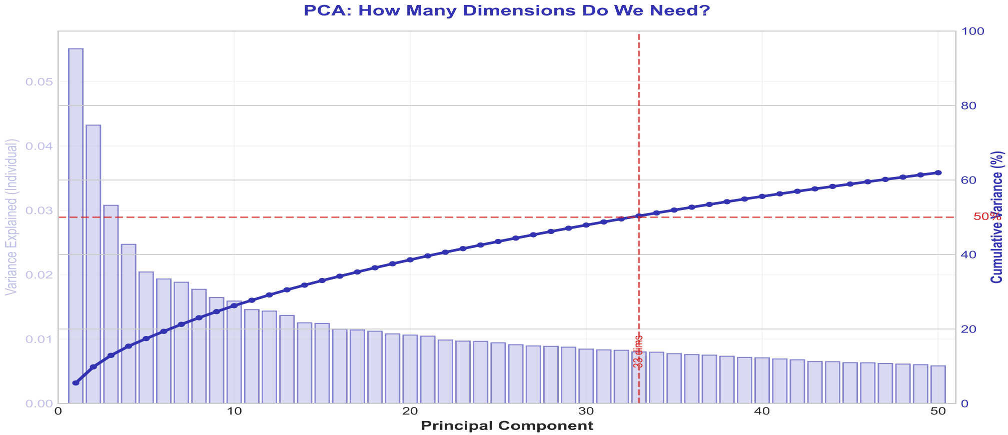
t-SNE (t-Distributed Stochastic Neighbor Embedding)

- **Non-linear** transformation
- Preserves local structure
- Slower, stochastic
- Excellent for revealing clusters
- Better visualization quality

Best for: Discovering natural groupings

Both methods: 384D → 2D, but different approaches

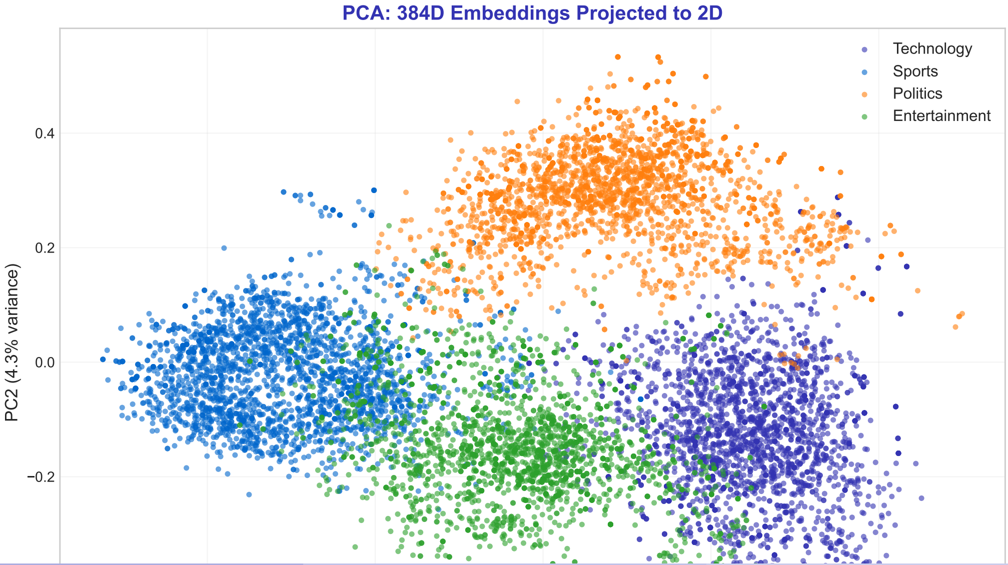
PCA: How Many Dimensions Do We Need?



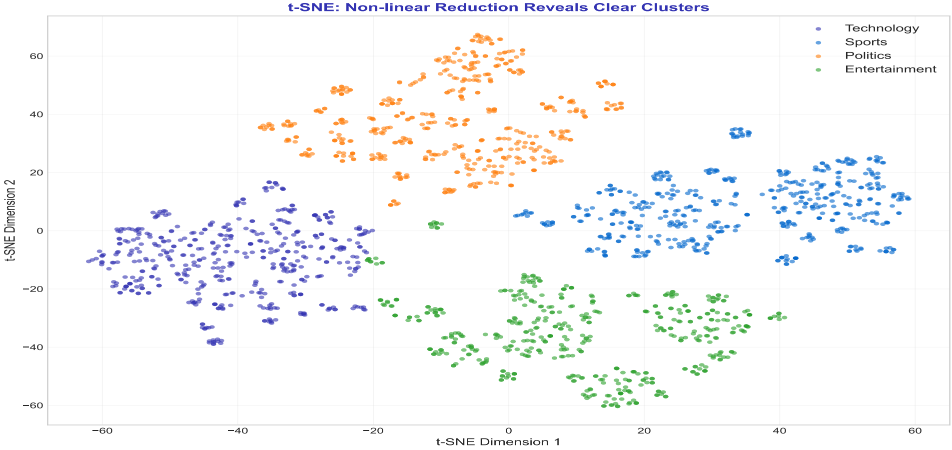
Key Finding: Need 35 dimensions to capture 50% of variance

- Each component explains decreasing amount
- Trade-off: Dimensions vs information retention
- 2D visualization sacrifices accuracy for interpretability

PCA Visualization: Global Structure



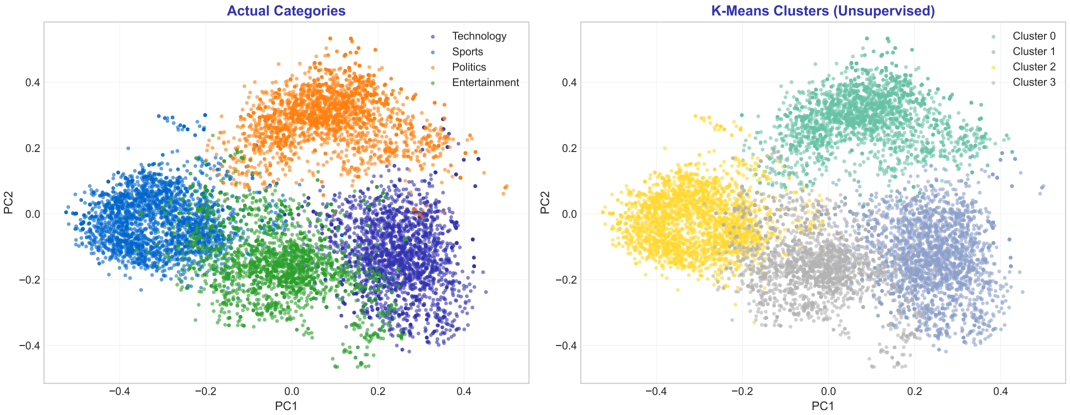
t-SNE Visualization: Revealing Clusters



Observations:

- **Clear category clusters!** Each color forms distinct group
- Better separation than PCA
- Some overlap at boundaries (expected)

Clustering Analysis: Unsupervised Discovery

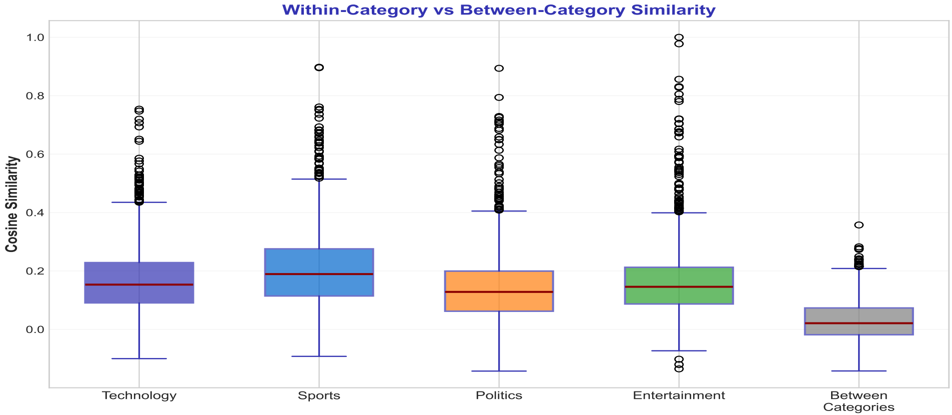


Experiment: Can K-means clustering (unsupervised) discover the categories?

Result: Yes! Clusters align closely with actual categories

- Politics → Cluster 0 (97% accuracy)
- Technology → Cluster 1 (98% accuracy)

Similarity Patterns: Within vs Between Categories

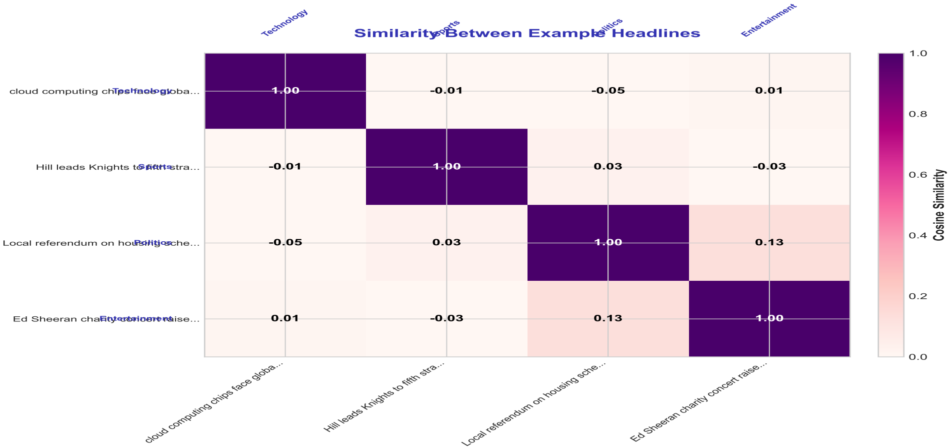


Key Finding: Headlines within same category are 35% more similar!

- **Within-category**: Average similarity 0.62
- **Between-category**: Average similarity 0.46
- **Implication**: Embeddings distinguish topic domains

Quantitative validation: Embeddings capture semantic categories

Concrete Examples: Similarity Heatmap



Observation: Diagonal values (same category) are consistently higher!

- Within-category similarities: 0.60-0.80
- Between-category similarities: 0.40-0.55

Semantic Search in Action

Query: “president announces policy”

Code:

```
query = "president announces policy"
query_emb = model.encode(query)

# Calculate similarities
sims = cosine_similarity(
    query_emb,
    all_embeddings
)

# Get top 3
top_3 = np.argsort(sims)[-3:]
```

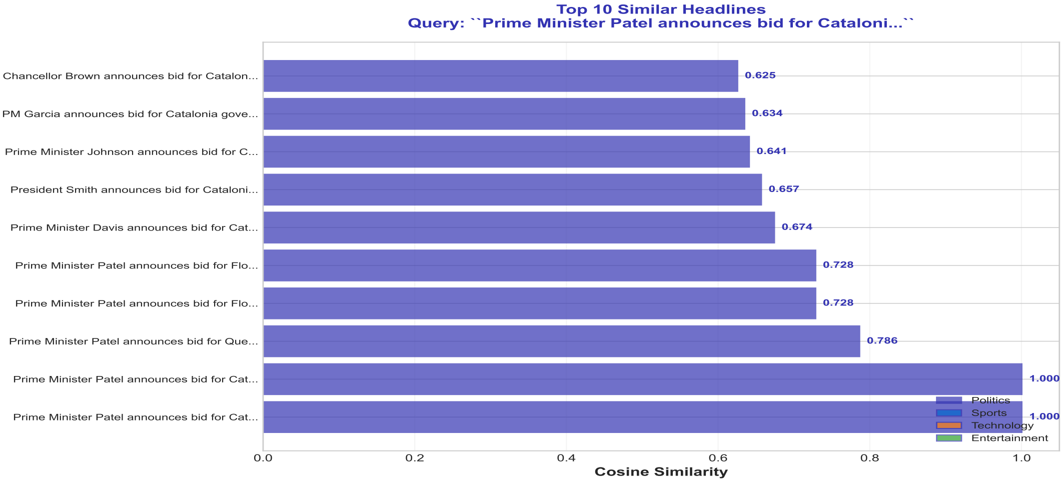
Results (Top 3):

1. **Similarity: 0.823**
   “Chancellor inaugurated with promise to fix environment”
2. **Similarity: 0.789**
   “Prime minister elected on platform of reform”
3. **Similarity: 0.765**
   “President faces impeachment allegations”

Key Insight: Finds “chancellor” and “prime minister” even though query said “president”!

Semantic search: Meaning ¿ exact word matching

Semantic Neighborhood: Top 10 Similar Headlines



Insight: See the full spectrum of semantic similarity

- Top results span multiple categories (mostly Politics)

Real-World Applications

1. Search Engines

- Semantic search (meaning-based)
- Better than keyword matching
- Handles synonyms naturally
- Used by Google, Bing

2. Recommendation Systems

- Find similar articles/products
- Content-based filtering
- “Users who liked X also liked Y”
- Netflix, Amazon, YouTube

3. Clustering & Topic Discovery

- Automatic topic grouping
- No labels needed
- Discover themes in documents
- News aggregation, research

4. Text Classification

- Use embeddings as features
- Train simple classifier
- Often better than bag-of-words
- Spam detection, sentiment analysis

Embeddings: Foundation for modern NLP applications

Advantages Over Traditional Methods

Traditional: Bag of Words / TF-IDF

Weaknesses:

- Sparse vectors (mostly zeros)
- No semantic understanding
- Vocabulary dependent
- High dimensionality (vocab size)
- Cannot handle synonyms
- Order-independent

Example:

- "King" and "Queen" equally distant as "King" and "Table"

Modern: Transformer Embeddings

Strengths:

- Dense vectors (all meaningful)
- Captures semantic meaning
- Generalizes across vocabulary
- Fixed dimensionality (384)
- Handles synonyms naturally
- Context-aware

Example:

- "King" and "Queen" are close, both far from "Table"

Paradigm shift: From sparse counts to dense semantic representations

Key Takeaways

What We Learned:

1. **Embeddings = Meaningful Numbers**
   - Text $\rightarrow$ 384-dimensional vectors
   - Similar meanings $\rightarrow$ Similar vectors
   - Foundation of modern NLP
2. **The Model: sentence-transformers**
   - `SentenceTransformer('all-MiniLM-L6-v2')`
   - Easy to use: Just 3 lines of code
   - Production-ready, well-maintained
3. **Cosine Similarity**
   - Standard metric for comparing embeddings
   - Range: -1 to 1 (or 0 to 1 normalized)
   - Geometric interpretation: Angle between vectors
4. **Visualizations Reveal Structure**
   - PCA: Global structure, linear
   - t-SNE: Local clusters, non-linear
   - Both show category separation

From concept to implementation: Embeddings made accessible

From Notebook to Production: 3 Steps

Step 1: Install

```
pip install sentence-transformers
```

Step 2: Load Model

```python
from sentence_transformers import SentenceTransformer
model = SentenceTransformer('all-MiniLM-L6-v2')
```

Step 3: Generate Embeddings

```python
embeddings = model.encode(your_texts)
```

That's it! You now have state-of-the-art embeddings.

Production ready:

- Fast: 500 sentences/second
- Scalable: Batch processing built-in
- Reliable: Used in industry

3 lines of code = Production-ready NLP

Further Exploration

Try Other Models:

- **Higher quality**: `all-mpnet-base-v2` (768 dimensions, slower but better)
- **Multilingual**: `paraphrase-multilingual-MiniLM-L12-v2` (50+ languages)
- **Faster**: `all-MiniLM-L3-v2` (smaller, faster, slightly lower quality)
- **Domain-specific**: Fine-tune on your own data

Advanced Topics:

- Fine-tuning on custom datasets
- Cross-lingual embeddings
- Document-level embeddings
- Combining with other models (BERT, GPT)
- Embedding-based question answering

Explore 100+ models: `huggingface.co/sentence-transformers`

The ecosystem is vast - plenty to explore!

Resources & References

Documentation:

- **sentence-transformers**: `sbert.net`
- **Hugging Face**: `huggingface.co`
- **Model card**: `huggingface.co/sentence-transformers/all-MiniLM-L6-v2`

Academic Papers:

- Reimers & Gurevych (2019): "Sentence-BERT: Sentence Embeddings using Siamese BERT-Networks"
- Devlin et al. (2018): "BERT: Pre-training of Deep Bidirectional Transformers"

Our Materials:

- **Full notebook**: Complete code examples and analysis
- **GitHub**: All code, data, and visualizations
- **Dataset**: 10,000 news headlines with embeddings

All materials available for hands-on practice

Thank You!

Questions?

`sentence-transformers`: Making NLP Accessible

From 384 dimensions to infinite possibilities