Seminar 1: Fun with Word Embeddings (3 points)

Today we gonna play with word embeddings: train our own little embedding, load one from gensim model zoo and use it to visualize text corpora.

This whole thing is gonna happen on top of embedding dataset.

Requirements: `pip install --upgrade nltk gensim bokeh` , but only if you're running locally.

- **nltk** ⟶ Natural Language Toolkit (used for NLP tasks like tokenization, stemming, POS tagging, etc.).
- **gensim** ⟶ Library for topic modeling, word embeddings (Word2Vec, FastText), and similarity search.
- **bokeh** ⟶ Interactive visualization library for building dashboards and plots in the browser.

```
pip install --upgrade nltk gensim bokeh
```

```
Requirement already satisfied: nltk in /usr/local/lib/python3.12/dist-packages (3.9.1)
Collecting gensim
  Downloading gensim-4.3.3-cp312-cp312-manylinux_2_17_x86_64.manylinux2014_x86_64.whl.metadata (8.1 kB)
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Collecting scipy<1.14.0,>=1.7.0 (from gensim)
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Installing collected packages: numpy, scipy, gensim, bokeh
  Attempting uninstall: numpy
    Found existing installation: numpy 2.0.2
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      Successfully uninstalled numpy-2.0.2
  Attempting uninstall: scipy
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    Uninstalling scipy-1.16.2:
      Successfully uninstalled scipy-1.16.2
  Attempting uninstall: bokeh
    Found existing installation: bokeh 3.7.3
    Uninstalling bokeh-3.7.3:
      Successfully uninstalled bokeh-3.7.3
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opencv-python-headless 4.12.0.88 requires numpy<2.3.0,>=2; python_version >= "3.9", but you have numpy 1.26.4 which is incompatib
thinc 8.3.6 requires numpy<3.0.0,>=2.0.0, but you have numpy 1.26.4 which is incompatible.
opencv-python 4.12.0.88 requires numpy<2.3.0,>=2; python_version >= "3.9", but you have numpy 1.26.4 which is incompatible.
tsfresh 0.21.1 requires scipy>=1.14.0; python_version >= "3.10", but you have scipy 1.13.1 which is incompatible.
Successfully installed bokeh-3.8.0 gensim-4.3.3 numpy-1.26.4 scipy-1.13.1
WARNING: The following packages were previously imported in this runtime:
  [numpy]
You must restart the runtime in order to use newly installed versions.
```

RESTART SESSION

```
# download the data:
!wget https://www.dropbox.com/s/obaitrix9jyu84r/quora.txt?dl=1 -O ./quora.txt
# alternative download link: https://yadi.sk/i/BPQrUu1NaTduEw
```

```
--2025-09-30 03:38:21--  https://www.dropbox.com/s/obaitrix9jyu84r/quora.txt?dl=1
Resolving www.dropbox.com (www.dropbox.com)... 162.125.6.18, 2620:100:601c:18::a27d:612
Connecting to www.dropbox.com (www.dropbox.com)|162.125.6.18|:443... connected.
HTTP request sent, awaiting response... 302 Found
Location: https://www.dropbox.com/scl/fi/p0t2dw6oqs6oxpd6zz534/quora.txt?rlkey=bjupppwua4zmd4elz8octecy9&dl=1 [following]
--2025-09-30 03:38:21--  https://www.dropbox.com/scl/fi/p0t2dw6oqs6oxpd6zz534/quora.txt?rlkey=bjupppwua4zmd4elz8octecy9&dl=1
Reusing existing connection to www.dropbox.com:443.
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Location: https://uc186224e97d53a6153c87a48119.dl.dropboxusercontent.com/cd/0/inline/CyWkuaVHuvrCaCD7Cswor1KHZzW0ZyzFwSgGL7ruxxT3wI
--2025-09-30 03:38:21--  https://uc186224e97d53a6153c87a48119.dl.dropboxusercontent.com/cd/0/inline/CyWkuaVHuvrCaCD7Cswor1KHZzW0Zyz
Resolving uc186224e97d53a6153c87a48119.dl.dropboxusercontent.com (uc186224e97d53a6153c87a48119.dl.dropboxusercontent.com)... 162.12
```

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HTTP request sent, awaiting response... 200 OK
Length: 33813903 (32M) [application/binary]
Saving to: './quora.txt'

./quora.txt         100%[===================>]  32.25M  --.-KB/s    in 0.1s

2025-09-30 03:38:21 (262 MB/s) - './quora.txt' saved [33813903/33813903]
```

```
import numpy as np

data = list(open("./quora.txt", encoding="utf-8"))
data[50]
```

```
'What TV shows or books help you read people's body language?\n'
```

Tokenization: a typical first step for an nlp task is to split raw data into words. The text we're working with is in raw format: with all the punctuation and smiles attached to some words, so a simple str.split won't do.

Let's use `nltk` - a library that handles many nlp tasks like tokenization, stemming or part-of-speech tagging.

```
from nltk.tokenize import WordPunctTokenizer
tokenizer = WordPunctTokenizer()

print(tokenizer.tokenize(data[50]))
```

```
['What', 'TV', 'shows', 'or', 'books', 'help', 'you', 'read', 'people', "'", 's', 'body', 'language', '?']
```

✅ How it works

- It uses a **regular expression** internally:

```
\w+|[^\w\s]+
```

This means:

- `\w+` → match words (letters, digits, underscore).
- `[^\w\s]+` → match anything that is not a word character or whitespace (i.e., punctuation).

So the tokenizer treats punctuation as **separate tokens** instead of attaching them to words.

🔹 Example

```
from nltk.tokenize import WordPunctTokenizer

tokenizer = WordPunctTokenizer()
text = "Hello, world! I'm testing NLTK's tokenizer."

tokens = tokenizer.tokenize(text)
print(tokens)
```

Output:

```
['Hello', ',', 'world', '!', 'I', "'", 'm', 'testing', 'NLTK', "'", 's', 'tokenizer', '.']
```

Notice:

- `"I'm"` becomes `["I", "'", "m"]`.
- `"NLTK's"` becomes `["NLTK", "'", "s"]`.
- Punctuation like `,` and `!` are **separate tokens**.

🔹 When to use

- Useful if you want **fine-grained control** over words and punctuation (e.g., training models that need punctuation tokens).
- Less useful if you want **whole words only** — in that case, use `nltk.word_tokenize`.

```
Start coding or generate with AI.
```

```python
# TASK: lowercase everything and extract tokens with tokenizer.
# data_tok should be a list of lists of tokens for each line in data.

data_tok = [tokenizer.tokenize(line.lower()) for line in data]
data_tok[:5]
```

```
 'i',
 'get',
 'back',
 'with',
 'my',
 'ex',
 'even',
 'though',
 'she',
 'is',
 'pregnant',
 'with',
 'another',
 'guy',
 "'",
 's',
 'baby',
 '?'],
['what',
 'are',
 'some',
 'ways',
 'to',
 'overcome',
 'a',
 'fast',
 'food',
 'addiction',
 '?'],
['who',
 'were',
 'the',
 'great',
 'chinese',
 'soldiers',
 'and',
 'leaders',
 'who',
 'fought',
 'in',
 'ww2',
 '?'],
['what', 'are', 'zip', 'codes', 'in', 'the', 'bay', 'area', '?'],
['why',
 'was',
 'george',
 'rr',
 'martin',
 'critical',
 'of',
 'jk',
 'rowling',
 'after',
 'losing',
 'the',
 'hugo',
 'award',
 '?']]
```

```python
# ✅ Check 1: Ensure that each row in data_tok is a list (or tuple) of tokens
assert all(isinstance(row, (list, tuple)) for row in data_tok), \
    "please convert each line into a list of tokens (strings)"

# ✅ Check 2: Ensure that every element inside each row is a string (i.e., tokens are strings)
assert all(all(isinstance(tok, str) for tok in row) for row in data_tok), \
    "please convert each line into a list of tokens (strings)"

# Define a helper function to check if a token is composed entirely of Latin letters
is_latin = lambda tok: all('a' <= x.lower() <= 'z' for x in tok)

# ✅ Check 3: Ensure all Latin text is lowercased
# - Join tokens in each row into a single string
# - If it contains only Latin letters, verify that it is lowercase
```

```
assert all(
    map(lambda line: not is_latin(line) or line.islower(), map(' '.join, data_tok))
), "please make sure to lowercase the data"

```

```
print([' '.join(row) for row in data_tok[:2]])
```

```
["can i get back with my ex even though she is pregnant with another guy ' s baby ?", 'what are some ways to overcome a fast food a
```

Word vectors: as the saying goes, there's more than one way to train word embeddings. There's Word2Vec and GloVe with different objective functions. Then there's fasttext that uses character-level models to train word embeddings.

The choice is huge, so let's start someplace small: **gensim** is another nlp library that features many vector-based models incuding word2vec.

🔹 Word2Vec Training Process

Word2Vec is a **shallow neural network** that learns to predict word-context relationships. There are two main architectures:

1. **CBOW (Continuous Bag of Words)**
   - Input: a group of context words
   - Output: the target word
   - Example: for the sentence `"The cat sat on the mat"`, if the target is `"sat"`, the model uses `["the", "cat", "on", "the"]` to predict `"sat"`.
2. **Skip-Gram**
   - Input: the target word
   - Output: predict surrounding context words
   - Example: with target `"sat"`, the model tries to predict `["the", "cat", "on", "the"]`.

👉 In **gensim**, the default is **CBOW** (`sg=0`). You can switch to Skip-Gram with `sg=1`.

🔹 Role of the Context Window

The `window` **parameter** defines how many words before and after the target word are considered as context.

Example sentence:

```
"The cat sat on the mat"
```

If:

- `window=2`
- Target word = `"sat"`

Then context = `[ "the", "cat", "on", "the" ]` (2 before, 2 after).

Intuition:

- **Small window (e.g., 2–5)** → captures **syntactic/functional similarity** (words that occur in similar grammatical roles).
  - `"run"` and `"walk"` may be close because they often occur in the same short-range contexts.
- **Large window (e.g., 10)** → captures **semantic similarity** (words about similar topics).
  - `"doctor"` and `"hospital"` may be close, even if they aren't side-by-side.

🔹 Optimization Objective

Word2Vec learns embeddings by maximizing the probability of predicting the right context words. The probability of a context word given a target word is defined using **softmax**:

Skip-gram Softmax Probability

$$P(w_O \mid w_I) = \frac{\exp\left(v'_{w_O} \cdot v_{w_I}\right)}{\sum_{w=1}^{V} \exp\left(v'_w \cdot v_{w_I}\right)}$$

- v_{w_I}: embedding vector of the **input (target) word**
- v'_{w_O}: embedding vector of the **output (context) word**
- V: size of the vocabulary

Since computing the denominator for all words is expensive, Word2Vec uses:

- **Negative Sampling** (default in gensim)
- Or **Hierarchical Softmax** (optional)

🔹 In gensim

When you train:

```
model = Word2Vec(
    sentences=data_tok,
    vector_size=32,
    window=5,     # context window
    min_count=5,
    sg=1          # use skip-gram (set to 0 for CBOW)
)
```

- Each training step picks a **target word**.
- Collects `window` words on each side as **positive context pairs**.
- Also generates random **negative samples** (words unlikely to be in context).
- Updates embeddings so positive pairs are closer and negative pairs are farther.

🔹 Example in practice

If your sentence is:

```
"I enjoy drinking hot coffee every morning"
```

With `window=2`, and `sg=1` (skip-gram):

- Target = `"drinking"`
- Context pairs = `[("drinking", "I"), ("drinking", "enjoy"), ("drinking", "hot"), ("drinking", "coffee")]`
- Plus negative samples like `("drinking", "car")`, `("drinking", "banana")`

The model learns:

- `"drinking"` is close to `"coffee"`, `"tea"`, `"beverage"` in vector space.

✅ In short:

- The **context window** decides how much "neighborhood" the model considers.
- **Training** nudges vectors so that words appearing in similar contexts end up close together in embedding space.

🔹 Classical Word2Vec (theory)

- In the **original papers**, the input word is represented as a **one-hot vector** of length = vocabulary size.
- If vocab size (V = 100{,}000), that vector would look like: `[0, 0, 0, ... 1 ... 0, 0]` (100k elements, mostly zeros).
- Multiplying this one-hot by the weight matrix (W \in \mathbb{R}^{V \times N}) simply **selects one row** (the embedding of that word).

👉 But storing and multiplying full one-hot vectors would be **hugely wasteful**.

🔹 What gensim does in practice

- Instead of actually creating one-hot vectors, gensim uses the **word's integer index** (its ID in the vocabulary).
- Example:
  - `"cat"` = index 512
  - `"dog"` = index 1337
- Then gensim just **looks up row 512 of (W)**, instead of multiplying a giant one-hot.

So:

- **One-hot vectors are conceptual only**.
- In reality, gensim keeps:
  - An **embedding matrix (W)** (shape (V \times N))
  - A **vocabulary dictionary** mapping word → index

When training, gensim:

1. Finds the integer index of the word (via vocab dict).
2. Directly fetches the corresponding row from the embedding matrix.

🔹 Where things are stored

- Vocabulary mapping: `model.wv.key_to_index` (word → index)
- Embedding matrix: `model.wv.vectors` (NumPy array, shape `[V, N]`)

Example:

```
print(model.wv.key_to_index["dog"])   # e.g. 1337
print(model.wv.vectors.shape)         # (V, 32)
print(model.wv["dog"].shape)          # (32,) → embedding of "dog"
```

✅ So to answer you directly:

- **One-hot vectors are never stored** (they are just an idea for how the math works).
- Gensim replaces them with **efficient integer indexing** into the embedding matrix.

```
Start coding or generate with AI.
```

```
from gensim.models import Word2Vec

# Train Word2Vec model
model = Word2Vec(
    sentences=data_tok,   # your tokenized sentences
    vector_size=32,       # embedding vector size
    window=5,             # context window size
    min_count=5,          # ignore words with total frequency < 5
    workers=4             # parallelization (set based on CPU cores)
)

# Access the KeyedVectors (word vectors)
wv = model.wv

```

```
# now you can get word vectors !
wv['coffee']
```

```
array([-2.0423462e+00, -2.0054679e+00, -1.4333248e-01, -7.4365938e-01,
       -1.1975869e+00, -1.5953760e+00,  2.2534728e+00,  4.5905414e-01,
        6.1650330e-01,  5.6228459e-01, -7.2874767e-03, -3.8930950e-01,
        7.4759072e-01,  1.6197788e+00,  4.9388221e-01,  4.0008952e-03,
        4.0123084e-01, -3.4540956e+00, -4.1496201e+00, -8.3979434e-01,
       -9.5983362e-01,  1.1993283e+00, -3.5154718e-01, -1.8843369e+00,
        1.5084225e+00,  4.9478003e-01, -1.0617627e-01, -1.1786098e+00,
        1.3009177e+00,  7.8300214e-01, -9.7595036e-01,  1.6359425e+00],
      dtype=float32)
```

```
# or query similar words directly. Go play with it!
wv.most_similar('bread')
```

```
[('rice', 0.9530182480812073),
 ('soup', 0.9298695921897888),
 ('sauce', 0.9286038875579834),
 ('cheese', 0.9179543852806091),
 ('chocolate', 0.915020227432251),
 ('corn', 0.9141954183578491),
 ('butter', 0.9092555642127991),
 ('fruit', 0.9048038721084595),
 ('beans', 0.9030898809432983),
 ('chicken', 0.9018431901931763)]
```

Using pre-trained model

Took it a while, huh? Now imagine training life-sized (100~300D) word embeddings on gigabytes of text: wikipedia articles or twitter posts.

Thankfully, nowadays you can get a pre-trained word embedding model in 2 lines of code (no sms required, promise).

```
import gensim.downloader as api
model = api.load('glove-twitter-100')
```

```
[==================================================] 100.0% 387.1/387.1MB downloaded
```

Nice 🎯 — you're now stepping into how to **query semantic relationships** from your trained Word2Vec model. Let's break down exactly what

```
model.most_similar(positive=["coder", "money"], negative=["brain"])
```

does:

🔹 1. Vector arithmetic

- Each word has an embedding vector, e.g.
  - (v_{\text{coder}})
  - (v_{\text{money}})
  - (v_{\text{brain}})
- Gensim computes:

[v_{\text{query}} = v_{\text{coder}} + v_{\text{money}} - v_{\text{brain}}]

This is the "analogy vector".

🔹 2. Similarity search

- Then it finds the **most similar words** (by cosine similarity) to this new vector (v_{\text{query}}).

🔹 3. Result

The output will be a **list of tuples** like:

```
[("developer", 0.72), ("startup", 0.68), ("salary", 0.65), ...]
```

- Each entry = `(word, similarity_score)`
- The words are ranked by how close their embeddings are to the computed query vector.

🔹 4. Intuition

You're basically asking:

> *"Which word is to `coder` and `money` as something else is to `brain`?"*

Or rephrased:

> *"What concept do I get if I combine coder + money but remove brain?"*

⚡ This is the same trick behind famous analogies like:

```
model.most_similar(positive=["king", "woman"], negative=["man"])
# → [('queen', 0.73), ...]
```

Would you like me to also show you **how to visualize this vector arithmetic** (e.g., plotting coder, money, brain, and the result on a 2D PCA plot)? That way you'd literally see how the subtraction/addition moves the vectors.

```
model.most_similar(positive=["coder", "money"], negative=["brain"])
```

```
[('broker', 0.5820155739784241),
 ('bonuses', 0.5424473285675049),
 ('banker', 0.5385112762451172),
 ('designer', 0.5197198390960693),
 ('merchandising', 0.4964233338832855),
 ('treet', 0.4922019839286804),
 ('shopper', 0.4920562207698822),
 ('part-time', 0.4912828207015991),
 ('freelance', 0.4843311905860901),
 ('aupair', 0.4796452522277832)]
```

Visualizing word vectors

One way to see if our vectors are any good is to plot them. Thing is, those vectors are in 30D+ space and we humans are more used to 2-3D.

Luckily, we machine learners know about **dimensionality reduction** methods.

Let's use that to plot 1000 most frequent words

```
# Get the top 1000 most frequent words from the model's vocabulary

# Step 1: Sort all words in the vocabulary
words = sorted(
    model.key_to_index.keys(),             # all words in the vocabulary
    key=lambda word: model.get_vecattr(word, "count"),  # sort by how many times the word appeared in training
    reverse=True                           # sort in descending order (most frequent first)
)[:1000]                                   # take only the top 1000 words

# Step 2: Print every 100th word (0th, 100th, 200th, ..., 900th)
print(words[::100])
```

```
['<user>', '_', 'please', 'apa', 'justin', 'text', 'hari', 'playing', 'once', 'sei']
```

```
print(words[:5])
```

```
['<user>', '.', ':', 'rt', ',']
```

```
Start coding or generate with AI.
```

```
# For each word in the vocabulary, get its vector representation
word_vectors = {word: model[word] for word in model.key_to_index.keys()}

# Example: print the vector of the word "king"
print(word_vectors["king"])
```

Explanation:

- `model[word]` → returns the embedding vector (a NumPy array) of that word.

- `model.key_to_index.keys()` → iterates through all words in the vocabulary.
- The dictionary comprehension `{word: model[word] for word in ...}` → builds a dictionary mapping each word to its vector.

⚡ If you want *just the vectors* (without word keys), you can also do:

```
word_vectors = model.vectors  # a NumPy array of shape (vocab_size, embedding_dim)
```

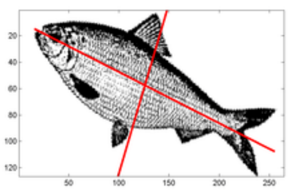
```
# For each word in the vocabulary, get its vector representation
word_vectors = np.array([model[word] for word in words])
```

```
assert isinstance(word_vectors, np.ndarray)
assert word_vectors.shape == (len(words), 100)
assert np.isfinite(word_vectors).all()
```

Linear projection: PCA

The simplest linear dimensionality reduction method is __P__rincipial __C__omponent __A__nalysis.

In geometric terms, PCA tries to find axes along which most of the variance occurs. The "natural" axes, if you wish.



Under the hood, it attempts to decompose object-feature matrix X into two smaller matrices: W and $\hat{W}$ minimizing *mean squared error*:

$$\|(XW)\hat{W} - X\|_2^2 \to_{W,\hat{W}} \min$$

- $X \in \mathbb{R}^{n \times m}$ - object matrix (**centered**);
- $W \in \mathbb{R}^{m \times d}$ - matrix of direct transformation;
- $\hat{W} \in \mathbb{R}^{d \times m}$ - matrix of reverse transformation;
- n samples, m original dimensions and d target dimensions;

1. What PCA does

- Word embeddings usually have **high dimensionality** (e.g., 100, 300, 768 dimensions).
- To **visualize** them on a 2D plane (scatter plot), we need to **reduce their dimensionality**.
- **PCA** is a mathematical technique that projects data into a lower-dimensional space while keeping as much variance (information) as possible.

---

2. How PCA works (intuitively)

- Imagine your data points are clouds of dots in 100D space.
- PCA finds **new axes (principal components)** such that:
  - The **first axis (PC1)** captures the most variance in the data.
  - The **second axis (PC2)** captures the next most variance, orthogonal to PC1.
- By keeping only the first 2 axes, you can **plot words in 2D** and still see meaningful relationships.

---

3. Why normalize after PCA

- After PCA, the projected vectors can have arbitrary scale and offset.
- Normalizing to **zero mean and unit variance** ensures that:
  - No axis dominates the visualization due to scaling.
  - The scatter plot is centered and comparable across different runs.

```
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler

# Step 1: Reduce to 2D with PCA
```

```python
pca = PCA(n_components=2)
word_vectors_pca = pca.fit_transform(word_vectors)

# Step 2: Normalize (zero mean, unit variance)
scaler = StandardScaler()
word_vectors_pca = scaler.fit_transform(word_vectors_pca)

print("Word vectors after PCA:", word_vectors_pca.shape)
print("Mean (should be ~0):", word_vectors_pca.mean(axis=0))
print("Std (should be ~1):", word_vectors_pca.std(axis=0))
```

```
Word vectors after PCA: (1000, 2)
Mean (should be ~0): [-2.7477741e-08  6.0945751e-09]
Std (should be ~1): [1.0000004 1.       ]
```

```python
assert word_vectors_pca.shape == (len(word_vectors), 2), "there must be a 2d vector for each word"
assert max(abs(word_vectors_pca.mean(0))) < 1e-5, "points must be zero-centered"
assert max(abs(1.0 - word_vectors_pca.std(0))) < 1e-2, "points must have unit variance"
```

Let's draw it!

```
import bokeh.models as bm, bokeh.plotting as pl
from bokeh.io import output_notebook

# Make sure Bokeh outputs plots directly inside the notebook
output_notebook()

def draw_vectors(x, y, radius=10, alpha=0.25, color='blue',
                 width=600, height=400, show=True, **kwargs):
    """
    Draws an interactive scatter plot for word vectors (or any 2D data).
    Includes hover info for extra metadata (like word labels).

    Parameters:
    - x, y: coordinates of points (e.g., PCA-reduced embeddings)
    - radius: point size
    - alpha: transparency
    - color: point color (single string or list of colors)
    - width, height: figure size
    - show: whether to display the plot immediately
    - **kwargs: additional metadata to display on hover (e.g., words)
    """

    # If a single color is given (e.g., "blue"), broadcast it to all points
    if isinstance(color, str):
        color = [color] * len(x)

    # Create a Bokeh ColumnDataSource to store data for plotting
    # This ties together x, y, color, and any extra info for hover display
    data_source = bm.ColumnDataSource({
        'x' : x,
        'y' : y,
        'color': color,
        **kwargs
    })

    # Create a figure with zoom enabled via mouse wheel
    fig = pl.figure(active_scroll='wheel_zoom', width=width, height=height)

    # Add scatter points to the figure
    fig.scatter('x', 'y', size=radius, color='color', alpha=alpha, source=data_source)

    # Add hover tooltips: show metadata (from kwargs) when hovering over points
    fig.add_tools(bm.HoverTool(tooltips=[(key, "@" + key) for key in kwargs.keys()]))

    # Show the plot if requested
    if show:
        pl.show(fig)

    # Return the figure object (so you can reuse or modify later)
    return fig

```

```
draw_vectors(word_vectors_pca[:, 0], word_vectors_pca[:, 1], token=words)

# hover a mouse over there and see if you can identify the clusters
```

figure(id = 'p1064', …)

Visualizing neighbors with t-SNE

PCA is nice but it's strictly linear and thus only able to capture coarse high-level structure of the data.

If we instead want to focus on keeping neighboring points near, we could use TSNE, which is itself an embedding method. Here you can read [more on TSNE](#).

1. What is t-SNE?

t-SNE (t-distributed Stochastic Neighbor Embedding) is a **non-linear dimensionality reduction** algorithm designed for visualization.

- PCA finds **global directions of variance** (linear projections).
- t-SNE focuses on **local neighborhoods**: it tries to keep *similar points close together* and *dissimilar points far apart* in the 2D (or 3D) space.

That’s why t-SNE usually produces clusters where similar words or phrases group tightly.

---

2. How t-SNE works (intuition)

1. Start with high-dimensional vectors (e.g., 100D word embeddings).
2. Compute **pairwise similarities** between points based on probability distributions.
   - Similar items → high probability.
   - Dissimilar items → low probability.
3. Map data into 2D/3D and **adjust positions** so the similarity structure is preserved.
   - Uses a **“student-t distribution”** to prevent distant points from crowding together.
4. The result: clusters are more visually separated than PCA.

---

3. Why normalize after t-SNE

- Just like PCA, the output of t-SNE can be shifted or scaled arbitrarily.
- Normalization (zero mean, unit variance) makes the visualization **balanced** and easy to interpret.

---

4. Your code (annotated)

```
from sklearn.manifold import TSNE
from sklearn.preprocessing import StandardScaler

# Step 1: Initialize t-SNE (map to 2D for visualization)
tsne = TSNE(n_components=2, random_state=42, perplexity=30, n_iter=1000)
```

```
# Step 2: Fit-transform word vectors
word_tsne = tsne.fit_transform(word_vectors)

# Step 3: Normalize results (zero mean, unit variance)
scaler = StandardScaler()
word_tsne = scaler.fit_transform(word_tsne)
```

---

5. PCA vs. t-SNE for embeddings

Aspect	PCA 📊	t-SNE 🎨
Type	Linear projection	Non-linear, probabilistic
Goal	Preserve global variance	Preserve local neighborhoods
Speed	Fast	Much slower
Interpretability	Easy (directions = principal components)	Harder (no simple axes meaning)
Visualization	Rough clusters, overlaps	Clear clusters, separation

---

```
from sklearn.manifold import TSNE
from sklearn.preprocessing import StandardScaler

# Initialize t-SNE to reduce embeddings from 100 dimensions → 2 dimensions
# - n_components=2: we want 2D output for visualization
# - random_state=42: for reproducibility
# - init="pca": initialize with PCA for faster convergence
# - perplexity=30: balances local vs. global structure (acts like neighborhood size)
# - n_iter=1000: number of optimization iterations (t-SNE needs many steps)
tsne = TSNE(n_components=2, random_state=42, init="pca", perplexity=30, n_iter=1000)

# Fit t-SNE on the word vectors and transform them into 2D coordinates
word_tsne = tsne.fit_transform(word_vectors)

# Normalize the resulting 2D vectors so they have zero mean and unit variance
# This makes plots more stable and comparable across different runs
word_tsne = StandardScaler().fit_transform(word_tsne)

print("t-SNE word vectors shape:", word_tsne.shape)  # should be (len(words), 2)
```

```
/usr/local/lib/python3.12/dist-packages/sklearn/manifold/_t_sne.py:1164: FutureWarning: 'n_iter' was renamed to 'max_iter' in versi
  warnings.warn(
t-SNE word vectors shape: (1000, 2)
```

```
draw_vectors(word_tsne[:, 0], word_tsne[:, 1], color='green', token=words)
```


figure(id = 'p1170', …)

Visualizing phrases

Word embeddings can also be used to represent short phrases. The simplest way is to take **an average** of vectors for all tokens in the phrase with some weights.

This trick is useful to identify what data are you working with: find if there are any outliers, clusters or other artefacts.

Let's try this new hammer on our data!

```
def get_phrase_embedding(phrase):
    """
    Convert phrase to a vector by aggregating its word embeddings.
    """

    # Start with a zero vector of the correct embedding size
    vector = np.zeros([model.vector_size], dtype='float32')

    # Tokenize: lowercase the phrase and split into words
    tokens = tokenizer.tokenize(phrase.lower())

    # If `model` is a Word2Vec instance → embeddings are in model.wv
    # If `model` is already KeyedVectors → use model directly
    kv = model.wv if hasattr(model, "wv") else model

    # Collect embeddings for words that exist in the vocabulary
    valid_vectors = [kv[word] for word in tokens if word in kv]

    if valid_vectors:
        # Average embeddings
        vector = np.mean(valid_vectors, axis=0)

    return vector

```

```
vector = get_phrase_embedding("I'm very sure. This never happened to me before...")

assert np.allclose(vector[::10],
                   np.array([ 0.31807372, -0.02558171,  0.0933293 , -0.1002182 , -1.0278689 ,
                             -0.16621883,  0.05083408,  0.17989802,  1.3701859 ,  0.08655966],
                              dtype=np.float32))
```

```
# Let's only consider ~1000 phrases for the first run
chosen_phrases = data[::len(data) // 1000]

# Compute embeddings for each chosen phrase
# We use the get_phrase_embedding function you defined earlier
phrase_vectors = np.array([get_phrase_embedding(phrase) for phrase in chosen_phrases])

print("Phrase vectors shape:", phrase_vectors.shape)  # (1000, embedding_size)

```

```
Phrase vectors shape: (1001, 100)
```

```
assert isinstance(phrase_vectors, np.ndarray) and np.isfinite(phrase_vectors).all()
assert phrase_vectors.shape == (len(chosen_phrases), model.vector_size)
```

```
# map vectors into 2d space with pca, tsne or your other method of choice
# don't forget to normalize

phrase_vectors_2d = TSNE().fit_transform(phrase_vectors)

phrase_vectors_2d = (phrase_vectors_2d - phrase_vectors_2d.mean(axis=0)) / phrase_vectors_2d.std(axis=0)
```

```
draw_vectors(phrase_vectors_2d[:, 0], phrase_vectors_2d[:, 1],
             phrase=[phrase[:50] for phrase in chosen_phrases],
             radius=20,)
```

figure(id = 'p1223', …)

Finally, let's build a simple "similar question" engine with phrase embeddings we've built.

```
# compute vector embedding for all lines in data
data_vectors = np.array([get_phrase_embedding(l) for l in data])
```

```
import numpy as np

def find_nearest(query, k=10):
    """
    given text line (query), return k most similar lines from data, sorted from most to least similar
    similarity should be measured as cosine between query and line embedding vectors
    """

    # --- Step 1: Convert query into a vector using get_phrase_embedding ---
    query_vector = get_phrase_embedding(query)

    # Handle case where query has no words in vocabulary
    if np.all(query_vector == 0) and not any(get_phrase_embedding(w).any() for w in query.split()):
        return []

    # --- Step 2: Normalize vectors for cosine similarity ---
    query_vector = query_vector / np.linalg.norm(query_vector)
    data_norm = data_vectors / np.linalg.norm(data_vectors, axis=1, keepdims=True)

    # --- Step 3: Compute cosine similarity between query and all data vectors ---
    sims = np.dot(data_norm, query_vector)

    # --- Step 4: Get indices of top-k most similar phrases ---
    # argpartition is efficient for top-k selection
    top_k_idx = np.argpartition(-sims, k)[:k]
    # sort those indices by actual similarity score (highest first)
    top_k_idx = top_k_idx[np.argsort(-sims[top_k_idx])]

    # --- Step 5: Return the actual lines from data ---
    return [data[i] for i in top_k_idx]


# --- Test the function ---
results = find_nearest(query="How do i enter the matrix?", k=10)

print(''.join(results))
```