```
# Install gensim if not already installed
!pip install gensim

# For loading pre-trained word embeddings from external sources
import gensim.downloader as api

# For performing numerical operations, especially with arrays and matrices
import numpy as np

# For creating static, interactive, and animated visualizations in Python
import matplotlib.pyplot as plt

# For dimensionality reduction, specifically t-distributed Stochastic Neighbor Embedding
from sklearn.manifold import TSNE
```

```
Requirement already satisfied: gensim in /usr/local/lib/python3.12/dist-packages (4.4.0)
Requirement already satisfied: numpy>=1.18.5 in /usr/local/lib/python3.12/dist-packages (from gensim) (2.0.2)
Requirement already satisfied: scipy>=1.7.0 in /usr/local/lib/python3.12/dist-packages (from gensim) (1.16.3)
Requirement already satisfied: smart_open>=1.8.1 in /usr/local/lib/python3.12/dist-packages (from gensim) (7.5.0)
Requirement already satisfied: wrapt in /usr/local/lib/python3.12/dist-packages (from smart_open>=1.8.1->gensim) (2.1.1)
```

```
# Load a pre-trained GloVe model with 100 dimensions from the gensim API
# This model was trained on Wikipedia 2014 + Gigaword 5 text data
model = api.load("glove-wiki-gigaword-100")

# Print the total number of unique words present in the loaded model's vocabulary
print("Vocabulary size:", len(model.key_to_index))

# Display the word vector (embedding) for the word 'computer'
print("\nVector for word 'computer':\n")
print(model['computer'])
```

```
Vocabulary size: 400000

Vector for word 'computer':

[-1.6298e-01  3.0141e-01  5.7978e-01  6.6548e-02  4.5835e-01 -1.5329e-01
  4.3258e-01 -8.9215e-01  5.7747e-01  3.6375e-01  5.6524e-01 -5.6281e-01
  3.5659e-01 -3.6096e-01 -9.9662e-02  5.2753e-01  3.8839e-01  9.6185e-01
  1.8841e-01  3.0741e-01 -8.7842e-01 -3.2442e-01  1.1202e+00  7.5126e-02
  4.2661e-01 -6.0651e-01 -1.3893e-01  4.7862e-02 -4.5158e-01  9.3723e-02
  1.7463e-01  1.0962e+00 -1.0044e+00  6.3889e-02  3.8002e-01  2.1109e-01
 -6.6247e-01 -4.0736e-01  8.9442e-01 -6.0974e-01 -1.8577e-01 -1.9913e-01
 -6.9226e-01 -3.1806e-01 -7.8565e-01  2.3831e-01  1.2992e-01  8.7721e-02
  4.3205e-01 -2.2662e-01  3.1549e-01 -3.1748e-01 -2.4632e-03  1.6615e-01
  4.2358e-01 -1.8087e+00 -3.6699e-01  2.3949e-01  2.5458e+00  3.6111e-01
  3.9486e-02  4.8607e-01 -3.6974e-01  5.7282e-02 -4.9317e-01  2.2765e-01
  7.9966e-01  2.1428e-01  6.9811e-01  1.1262e+00 -1.3526e-01  7.1972e-01
 -9.9605e-04 -2.6842e-01 -8.3038e-01  2.1780e-01  3.4355e-01  3.7731e-01
 -4.0251e-01  3.3124e-01  1.2576e+00 -2.7196e-01 -8.6093e-01  9.0053e-02
 -2.4876e+00  4.5200e-01  6.6945e-01 -5.4648e-01 -1.0324e-01 -1.6979e-01
  5.9437e-01  1.1280e+00  7.5755e-01 -5.9160e-02  1.5152e-01 -2.8388e-01
  4.9452e-01 -9.1703e-01  9.1289e-01 -3.0927e-01]
```

```
# Define a list of words categorized by different themes (animals, fruits, countries, technology, vehicles, emotions)
# These words will be used to demonstrate word embedding visualization
words = [
    # Animals
    "dog","cat","lion","tiger","elephant","horse","cow","goat",

    # Fruits
    "apple","banana","mango","orange","grape","pineapple",

    # Countries
    "india","china","japan","germany","france","italy","canada",

    # Technology
    "computer","laptop","keyboard","mouse","internet","software","hardware",

    # Vehicles
    "car","bus","train","airplane","bicycle","motorcycle",

    # Emotions
    "happy","sad","angry","fear","love","joy"
]
```

```
# Extract the 100-dimensional word vectors for each word in the 'words' list
# These vectors are then stacked into a NumPy array
vectors = np.array([model[word] for word in words])
```

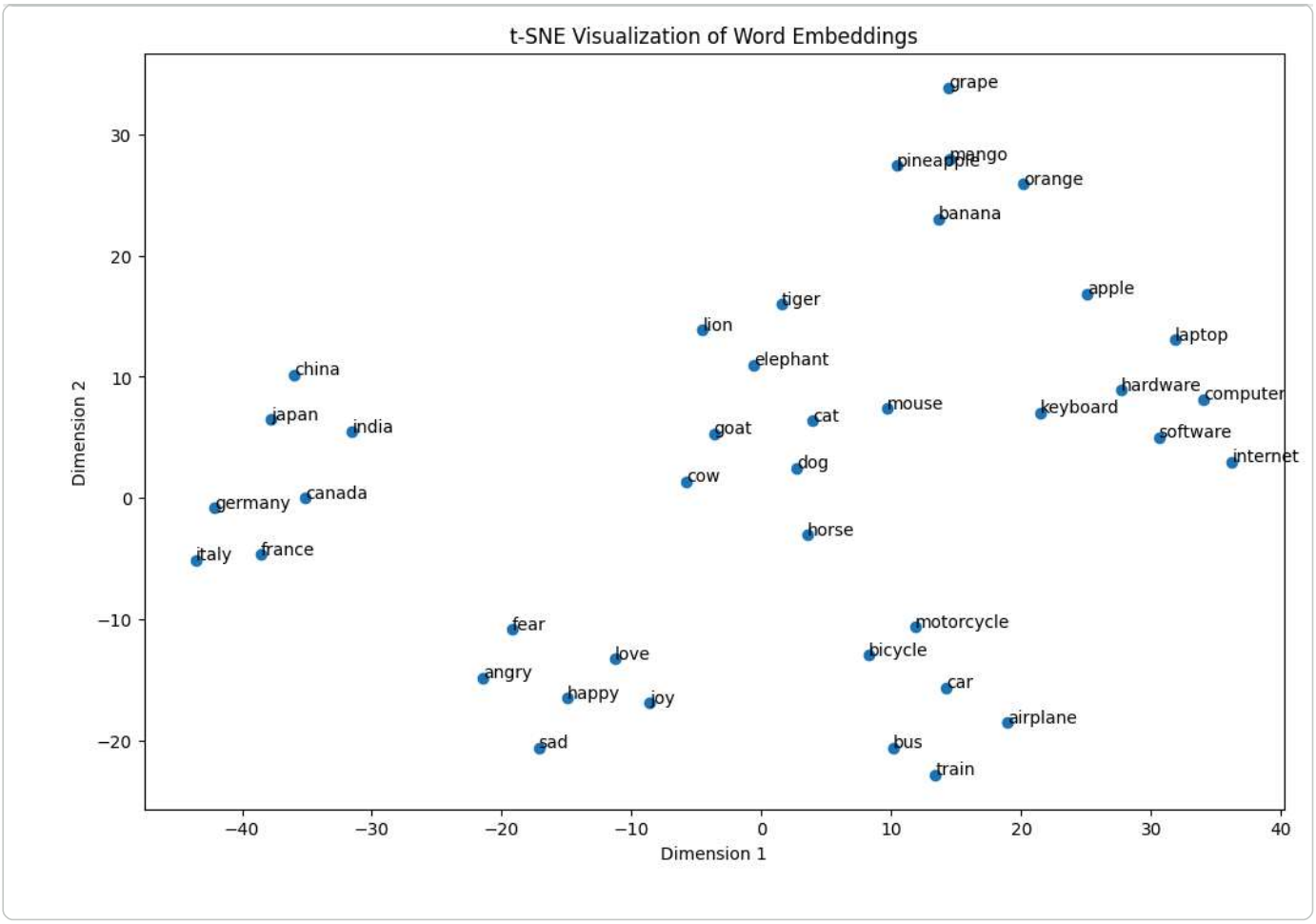
```
# Print the list of selected words that were used for extracting vectors
print("Selected Words:\n")
print(words)

# Print the total count of words selected
print("\nTotal words selected:", len(words))

# Print the shape of the 'vectors' NumPy array. It should be (number of words, embedding dimension)
print("\nShape of extracted vectors:", vectors.shape)

# Print the first 5 values of the word vector for the first word in the 'words' list (which is 'dog')
print("\nFirst 5 values of vector for word:", words[0])
print(vectors[0][:5])
```

```
Selected Words:

['dog', 'cat', 'lion', 'tiger', 'elephant', 'horse', 'cow', 'goat', 'apple', 'banana', 'mango', 'orange', 'grape', 'pineapple',

Total words selected: 40

Shape of extracted vectors: (40, 100)

First 5 values of vector for word: dog
[ 0.30817  0.30938  0.52803 -0.92543 -0.73671]
```

```
# Initialize a t-SNE model for dimensionality reduction
# n_components=2 means we want to reduce the vectors to 2 dimensions for visualization
# random_state=42 ensures reproducibility of the results
# perplexity=10 is a common hyperparameter for t-SNE, influencing how local and global aspects are balanced
tsne = TSNE(n_components=2, random_state=42, perplexity=10)

# Apply t-SNE to the high-dimensional word vectors to reduce them to 2 dimensions
reduced_vectors = tsne.fit_transform(vectors)

# Print the shape of the 'reduced_vectors' array, which should now be (number of words, 2)
print("Shape after reduction:", reduced_vectors.shape)
```

```
Shape after reduction: (40, 2)
```

```
# Create a new figure for the plot with a specified size (width=12 inches, height=8 inches)
plt.figure(figsize=(12,8))

# Extract the x-coordinates (first dimension) from the reduced vectors
x = reduced_vectors[:,0]
# Extract the y-coordinates (second dimension) from the reduced vectors
y = reduced_vectors[:,1]

# Create a scatter plot using the 2D reduced vectors
plt.scatter(x, y)

# Annotate each point in the scatter plot with its corresponding word
# This loop iterates through the index and word for each item in the 'words' list
for i, word in enumerate(words):
    # Place the word annotation at the (x[i], y[i]) coordinates
    plt.annotate(word, (x[i], y[i]))

# Set the title of the plot
plt.title("t-SNE Visualization of Word Embeddings")
# Set the label for the x-axis
plt.xlabel("Dimension 1")
# Set the label for the y-axis
plt.ylabel("Dimension 2")

# Display the plot
plt.show()
```


t-SNE Visualization of Word Embeddings
grape
pineapple
mango
orange
banana
apple
tiger
lion
laptop
elephant
china
hardware
computer
mouse
keyboard
japan
india
cat
goat
software
internet
dog
cow
germany
canada
horse
italy
france
fear
motorcycle
love
bicycle
angry
car
happy
joy
airplane
sad
bus
train
Dimension 1
Dimension 2
30
20
10
0
−10
−20
−40
−30
−20
−10
0
10
20
30
40