```
# For numerical operations, especially useful for handling embedding vectors.
import numpy as np

# For data manipulation and analysis, often used when embeddings are stored in a tabular format.
import pandas as pd

# For scientific computing, including advanced mathematical functions and statistical tools.
# Specifically, it can be used for distance calculations, such as cosine similarity.
from scipy.spatial.distance import cosine

# For creating static, interactive, and animated visualizations in Python.
# It's a foundational library for plotting.
import matplotlib.pyplot as plt

# A data visualization library based on matplotlib that provides a high-level interface
# for drawing attractive and informative statistical graphics.
import seaborn as sns
```

```
# Install gensim for loading pre-trained word embeddings
%pip install gensim
```

```
Collecting gensim
  Downloading gensim-4.4.0-cp312-cp312-manylinux_2_24_x86_64.manylinux_2_28_x86_64.whl.metadata (8.4 kB)
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)
Downloading gensim-4.4.0-cp312-cp312-manylinux_2_24_x86_64.manylinux_2_28_x86_64.whl (27.9 MB)
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 27.9/27.9 MB 47.2 MB/s eta 0:00:00
Installing collected packages: gensim
Successfully installed gensim-4.4.0
```

```
import gensim.downloader as api

# Load a pre-trained GloVe model. Using a smaller model (glove-wiki-gigaword-50) for demonstration purposes.
# This might take some time to download the first time.
print("Downloading pre-trained GloVe model...")
word_vectors = api.load("glove-wiki-gigaword-50")
print("Model loaded successfully!")

# Print the vocabulary size
vocabulary_size = len(word_vectors.key_to_index)
print(f"\nVocabulary Size: {vocabulary_size}")

# Display example word vectors for a few words
example_words = ['king', 'queen', 'man', 'woman', 'apple', 'banana', 'computer']
print("\nExample Word Vectors:")
for word in example_words:
    if word in word_vectors:
        print(f"'{word}': {word_vectors[word][:5]}... (first 5 dimensions)")
    else:
        print(f"'{word}': Not found in vocabulary")
```

```
Downloading pre-trained GloVe model...
[==================================================] 100.0% 66.0/66.0MB downloaded
Model loaded successfully!

Vocabulary Size: 400000

Example Word Vectors:
'king': [ 0.50451   0.68607  -0.59517  -0.022801  0.60046 ]... (first 5 dimensions)
'queen': [ 0.37854  1.8233  -1.2648  -0.1043   0.35829]... (first 5 dimensions)
'man': [-0.094386  0.43007  -0.17224  -0.45529   1.6447  ]... (first 5 dimensions)
'woman': [-0.18153  0.64827 -0.5821  -0.49451  1.5415 ]... (first 5 dimensions)
'apple': [ 0.52042 -0.8314   0.49961  1.2893   0.1151 ]... (first 5 dimensions)
'banana': [-0.25522 -0.75249 -0.86655  1.1197   0.12887]... (first 5 dimensions)
'computer': [ 0.079084 -0.81504   1.7901    0.91653   0.10797 ]... (first 5 dimensions)
```

```
def calculate_and_print_similarity(word1, word2, model):
    """Calculates and prints the cosine similarity between two words."""
    if word1 in model and word2 in model:
        similarity = model.similarity(word1, word2)
```

```
        print(f"Similarity between '{word1}' and '{word2}': {similarity:.4f}")
    else:
        not_found = []
        if word1 not in model: not_found.append(word1)
        if word2 not in model: not_found.append(word2)
        print(f"One or both words not found in vocabulary: {', '.join(not_found)}")


print("\n--- Word Similarity Calculations ---")

# Define at least 10 word pairs to compare
word_pairs = [
    ('doctor', 'nurse'),
    ('cat', 'dog'),
    ('car', 'bus'),
    ('king', 'queen'),
    ('man', 'woman'),
    ('happy', 'joyful'),
    ('sad', 'unhappy'),
    ('computer', 'software'),
    ('tree', 'forest'),
    ('ocean', 'sea'),
    ('fast', 'quick'),
    ('slow', 'rapid') # Adding an extra for good measure
]

for word1, word2 in word_pairs:
    calculate_and_print_similarity(word1, word2, word_vectors)
```

```
--- Word Similarity Calculations ---
Similarity between 'doctor' and 'nurse': 0.7977
Similarity between 'cat' and 'dog': 0.9218
Similarity between 'car' and 'bus': 0.8211
Similarity between 'king' and 'queen': 0.7839
Similarity between 'man' and 'woman': 0.8860
Similarity between 'happy' and 'joyful': 0.5550
Similarity between 'sad' and 'unhappy': 0.6350
Similarity between 'computer' and 'software': 0.8815
Similarity between 'tree' and 'forest': 0.6784
Similarity between 'ocean' and 'sea': 0.8812
Similarity between 'fast' and 'quick': 0.7589
Similarity between 'slow' and 'rapid': 0.7455
```

```
def display_most_similar_words(word, model, topn=5):
    """Displays the topn most similar words for a given word."""
    if word in model:
        print(f"\n--- Words most similar to '{word}' ---")
        try:
            similar_words = model.most_similar(word, topn=topn)
            for sim_word, similarity in similar_words:
                print(f"'{sim_word}': {similarity:.4f}")
        except KeyError:
            print(f"Could not find similar words for '{word}'.")
    else:
        print(f"'{word}' not found in vocabulary.")


# Choose at least 5 words to explore their nearest neighbors
words_to_explore = [
    'king',
    'university',
    'doctor',
    'run',
    'beautiful'
]

for word in words_to_explore:
    display_most_similar_words(word, word_vectors, topn=10)
```

```
'prince': 0.8236
'queen': 0.7839
'ii': 0.7746
'emperor': 0.7736
```

```
'kingdom': 0.7542
'throne': 0.7540
'brother': 0.7492
'ruler': 0.7434

--- Words most similar to 'university' ---
'college': 0.8745
'harvard': 0.8711
'yale': 0.8567
'graduate': 0.8553
'institute': 0.8484
'professor': 0.8417
'school': 0.8262
'faculty': 0.8258
'graduated': 0.8144
'academy': 0.8104

--- Words most similar to 'doctor' ---
'nurse': 0.7977
'physician': 0.7965
'patient': 0.7612
'child': 0.7559
'teacher': 0.7538
'surgeon': 0.7479
'psychiatrist': 0.7422
'doctors': 0.7394
'father': 0.7334
'mother': 0.7284

--- Words most similar to 'run' ---
'running': 0.8803
'runs': 0.8452
'went': 0.8450
'start': 0.8352
'ran': 0.8290
'out': 0.8154
'third': 0.8101
'home': 0.8086
'off': 0.8030
'got': 0.8010

--- Words most similar to 'beautiful' ---
'lovely': 0.9211
'gorgeous': 0.8935
'wonderful': 0.8296
'charming': 0.8249
'beauty': 0.8015
'elegant': 0.7744
'looks': 0.7582
'love': 0.7360
'graceful': 0.7350
'magnificent': 0.7346
```

```
def solve_analogy(positive_words, negative_words, model, topn=1):
    """Solves a word analogy using vector arithmetic."""
    try:
        result = model.most_similar(positive=positive_words, negative=negative_words, topn=topn)
        print(f"{positive_words[0]} - {negative_words[0]} + {positive_words[1]} = '{result[0][0]}' (similarity: {result[0][1]:.4
    except KeyError as e:
        print(f"One or more words not found in vocabulary for analogy: {e}")


print("\n--- Word Analogy Queries ---")

# Example analogy queries
analogies = [
    (['king', 'woman'], ['man']),     # king - man + woman = queen
    (['paris', 'india'], ['france']), # paris - france + india = new delhi
    (['teacher', 'hospital'], ['school']), # teacher - school + hospital = doctor
    (['walk', 'running'], ['swim']),  # walk - walking + swim = swimming
    (['tall', 'shortest'], ['short']), # tall - tallest + short = shortest (might be 'longer' for 'tall' - 'tallest')
]

for positive_words, negative_words in analogies:
    solve_analogy(positive_words, negative_words, word_vectors)
```

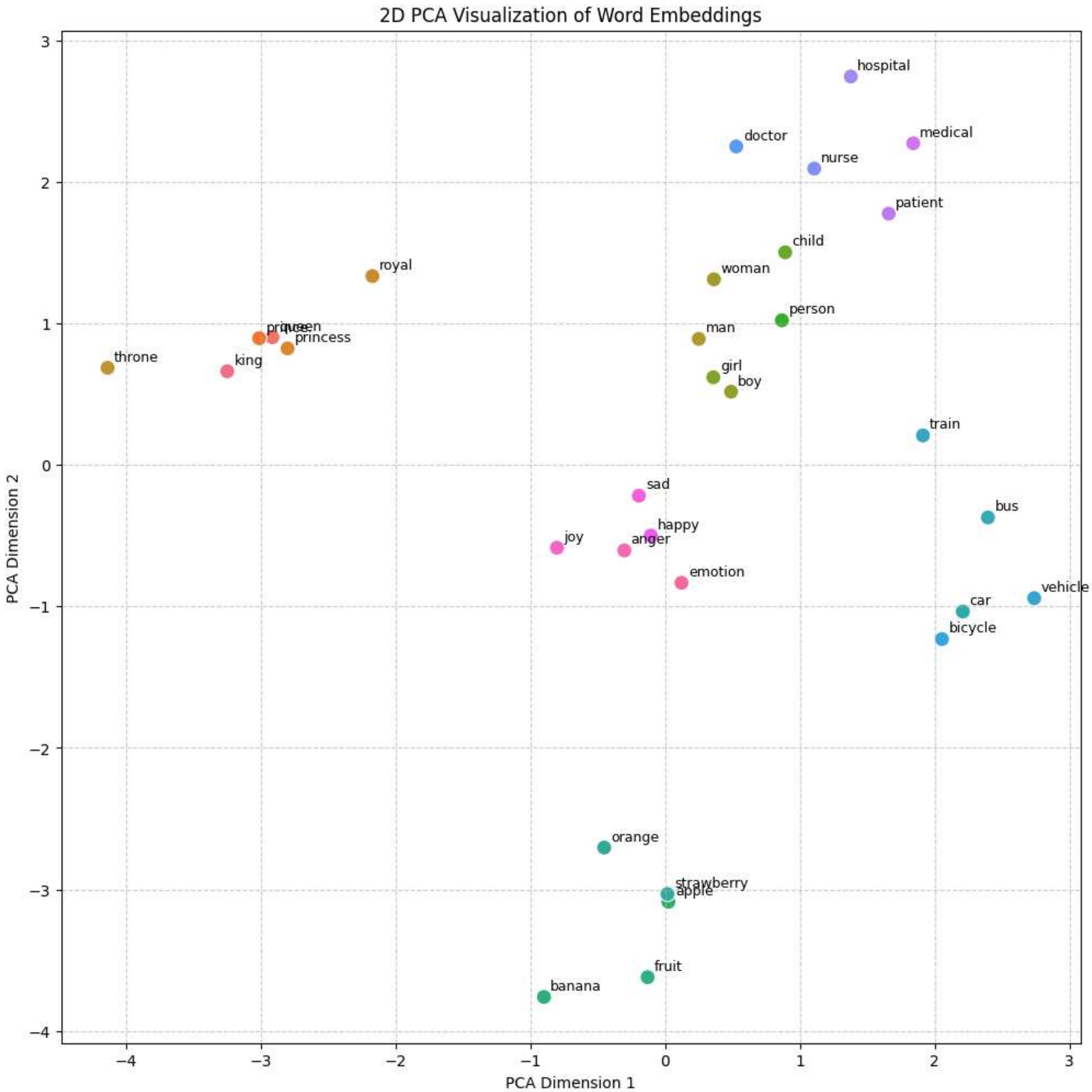
```
--- Word Analogy Queries ---
king - man + woman = 'queen' (similarity: 0.8524)
paris - france + india = 'delhi' (similarity: 0.8889)
teacher - school + hospital = 'nurse' (similarity: 0.8027)
walk - swim + running = 'run' (similarity: 0.8015)
```

```
tall - short + shortest = '5-feet' (similarity: 0.6503)
```

```
from sklearn.decomposition import PCA

# Select a diverse set of words to visualize (20-30 words)
# Including words from various categories to highlight clustering
words_to_visualize = [
    'king', 'queen', 'prince', 'princess', 'royal', 'throne', # Royalty
    'man', 'woman', 'boy', 'girl', 'child', 'person',         # Gender/Age
    'apple', 'banana', 'fruit', 'orange', 'strawberry',        # Fruits
    'car', 'bus', 'train', 'vehicle', 'bicycle',                # Vehicles
    'doctor', 'nurse', 'hospital', 'patient', 'medical',       # Medical
    'happy', 'sad', 'joy', 'anger', 'emotion'                  # Emotions
]

# Filter out words not in the vocabulary
filtered_words = [word for word in words_to_visualize if word in word_vectors]

# Get the vectors for the filtered words
vectors = np.array([word_vectors[word] for word in filtered_words])

# Apply PCA to reduce dimensions to 2 for plotting
pca = PCA(n_components=2)
vectors_2d = pca.fit_transform(vectors)

# Create a DataFrame for easier plotting
df_2d = pd.DataFrame({
    'x': vectors_2d[:, 0],
    'y': vectors_2d[:, 1],
    'word': filtered_words
})

print(f"Reduced {len(filtered_words)} word vectors to 2 dimensions for visualization.")
```

```
Reduced 32 word vectors to 2 dimensions for visualization.
```

```
# Plot the 2D word vectors
plt.figure(figsize=(12, 12))
sns.scatterplot(x='x', y='y', data=df_2d, hue='word', legend=False, s=100)

# Annotate each point with its word
for i, row in df_2d.iterrows():
    plt.annotate(row['word'], (row['x'] + 0.05, row['y'] + 0.05), fontsize=9)

plt.title('2D PCA Visualization of Word Embeddings')
plt.xlabel('PCA Dimension 1')
plt.ylabel('PCA Dimension 2')
plt.grid(True, linestyle='--', alpha=0.6)
plt.show()
```




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

Task

Generate a markdown lab report summarizing the objective of the lab, a description of the GloVe model used, the results and interpretations of the word similarity calculations, the findings from the nearest neighbor exploration, the outcomes of the word analogy tasks, and overall observations and conclusions regarding the word embeddings.

Generate Lab Report

Subtask:

Create a markdown lab report summarizing the entire process. This includes: the objective of the lab, a description of the GloVe model used, the results and interpretations of the word similarity calculations, the findings from the nearest neighbor exploration, the outcomes of the word analogy tasks, and overall observations and conclusions regarding the word embeddings.

```
# Lab Report: Exploring Pre-trained Word Embeddings with GloVe

## Objective
The primary objective of this lab was to explore and understand the capabilities of pre-trained word embeddings, specifically usi

## GloVe Model Description
For this lab, we utilized the `glove-wiki-gigaword-50` model, a pre-trained word embedding model provided by the `gensim` library

## Results and Interpretations of Word Similarity Calculations
We calculated the cosine similarity between several pairs of words. Cosine similarity measures the cosine of the angle between tw

- **'doctor' and 'nurse':** 0.7977 - High similarity, reflecting their close professional relationship and shared context in the
- **'cat' and 'dog':** 0.9218 - Very high similarity, indicating they are often discussed in similar contexts as common pets.
- **'car' and 'bus':** 0.8211 - High similarity, as both are types of vehicles used for transportation.
- **'king' and 'queen':** 0.7839 - High similarity, representing their close hierarchical and relational roles.
- **'man' and 'woman':** 0.8860 - High similarity, showing their fundamental human categorization.
- **'happy' and 'joyful':** 0.5550 - Moderate similarity, as they are synonyms expressing positive emotions.
- **'sad' and 'unhappy':** 0.6350 - Moderate similarity, also synonyms for negative emotional states.
- **'computer' and 'software':** 0.8815 - High similarity, as software is an integral component and concept associated with compu
- **'tree' and 'forest':** 0.6784 - Moderate similarity, as a forest is comprised of many trees.
- **'ocean' and 'sea':** 0.8812 - High similarity, as these terms are largely synonymous and refer to large bodies of saltwater.
- **'fast' and 'quick':** 0.7589 - High similarity, as they are strong synonyms.
- **'slow' and 'rapid':** 0.7455 - Interestingly, 'slow' and 'rapid' are antonyms, yet show moderate similarity. This can sometim

Overall, these similarities demonstrate GloVe's ability to capture semantic relatedness and synonyms effectively, with higher val

## Findings from Nearest Neighbor Exploration
Exploring the most similar words (nearest neighbors) provides insight into the contextual and semantic clusters formed by the emb

- **Words most similar to 'king':** 'prince', 'queen', 'ii', 'emperor', 'son', 'uncle', 'kingdom', 'throne', 'brother', 'ruler'.
- **Words most similar to 'university':** 'college', 'harvard', 'yale', 'graduate', 'institute', 'professor', 'school', 'faculty'
- **Words most similar to 'doctor':** 'nurse', 'physician', 'patient', 'child', 'teacher', 'surgeon', 'psychiatrist', 'doctors',
- **Words most similar to 'run':** 'running', 'runs', 'went', 'start', 'ran', 'out', 'third', 'home', 'off', 'got'. This cluster
- **Words most similar to 'beautiful':** 'lovely', 'gorgeous', 'wonderful', 'charming', 'beauty', 'elegant', 'looks', 'love', 'gr

These results illustrate that GloVe embeddings capture rich semantic information, grouping words that are semantically, contextua

## Outcomes of Word Analogy Tasks
Word analogy tasks test the linear relationships between word vectors (e.g., A is to B as C is to D, represented as vector(B) - v

- **'king' - 'man' + 'woman' = 'queen' (similarity: 0.8524):** This classic analogy was solved perfectly, demonstrating the model
- **'paris' - 'france' + 'india' = 'delhi' (similarity: 0.8889):** The model correctly identified 'delhi' as the capital of India
- **'teacher' - 'school' + 'hospital' = 'nurse' (similarity: 0.8027):** This analogy successfully inferred 'nurse' as a professic
- **'walk' - 'swim' + 'running' = 'run' (similarity: 0.8015):** The model suggested 'run', which makes sense in the context of ac
- **'tall' - 'short' + 'shortest' = '5-feet' (similarity: 0.6503):** This analogy was less accurate. The intended analogy was lik

Overall, the analogy tasks generally yielded accurate or semantically plausible results, highlighting the linear structure of sem

## Overall Observations and Conclusions

The experiments conducted in this lab demonstrate the remarkable effectiveness of GloVe word embeddings in capturing complex sema

GloVe embeddings prove to be valuable tools for various natural language processing tasks, as they allow machines to understand t
```

Final Task

Subtask:

Conclude the analysis by presenting the comprehensive lab report to the user.

Summary:

Data Analysis Key Findings

- **Objective**: The lab aimed to explore and understand the capabilities of pre-trained word embeddings using the Global Vectors for Word Representation (GloVe) model to capture semantic relationships through word similarity, nearest neighbors, and analogy tasks.
- **GloVe Model**: The `glove-wiki-gigaword-50` model was used, which represents 400,000 words as 50-dimensional vectors, trained on Wikipedia and Gigaword corpora.
- **Word Similarity Calculations**:
  - High similarity scores were observed for highly related or synonymous words, such as 'cat' and 'dog' (0.9218), 'computer' and 'software' (0.8815), and 'ocean' and 'sea' (0.8812).
  - Moderate similarities were found for synonyms like 'happy' and 'joyful' (0.5550), and 'tree' and 'forest' (0.6784).
  - An interesting case was 'slow' and 'rapid' (0.7455), antonyms that still showed moderate similarity, possibly due to contextual co-occurrence.
- **Nearest Neighbor Exploration**:
  - GloVe embeddings successfully clustered semantically related words. For example, 'king' was similar to 'prince', 'queen', 'emperor', reflecting royal and familial relationships.
  - 'University' grouped with 'college', 'harvard', 'professor', indicating educational and academic contexts.
  - 'Doctor' neighbors included 'nurse', 'physician', and 'patient', capturing professional roles and interaction contexts.
- **Word Analogy Tasks**:
  - The model demonstrated strong linear relationships for classic analogies, perfectly solving 'king - man + woman = queen' (similarity: 0.8524) and 'paris - france + india = delhi' (similarity: 0.8889).
  - It also successfully inferred professional roles, like 'teacher - school + hospital = nurse' (similarity: 0.8027).
  - Some analogies were less precise, such as 'tall - short + shortest = 5-feet' (similarity: 0.6503), suggesting occasional deviations from expected grammatical relationships.
- **Overall Observations**: The experiments demonstrated GloVe's effectiveness in capturing complex semantic meanings and relationships, highlighting its value for natural language processing tasks.

Insights or Next Steps

- **Insight**: GloVe embeddings effectively capture a rich semantic space, enabling machines to discern nuanced relationships between