Lab 3 - Part 2: Word and Sentence Embeddings

Objectives:

- Understand and implement Word2Vec (CBOW and Skip-gram)
- Work with pre-trained GloVe embeddings
- Use BERT for sentence embeddings
- Compare different embedding approaches
- Apply embeddings to find similar words and documents

Instructions

1. Complete all exercises marked with `# YOUR CODE HERE`
2. **Answer all written questions** in the designated markdown cells
3. Save your completed notebook
4. **Push to your Git repository and send the link to:** yoroba93@gmail.com

Important: This lab continues from Part 1

You will use the same dataset and categories you chose in Part 1.

Setup

```
# Install required libraries (uncomment if needed)
# !pip install gensim transformers torch sentence-transformers datasets
!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) (2.0.1)
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 43.3 MB/s eta 0:00:00
Installing collected packages: gensim
Successfully installed gensim-4.4.0
```

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from collections import Counter
import re
import string
import warnings
warnings.filterwarnings('ignore')

import nltk
nltk.download('punkt', quiet=True)
nltk.download('stopwords', quiet=True)
nltk.download('wordnet', quiet=True)
nltk.download('punkt_tab', quiet=True) # Added to fix the LookupError

from nltk.tokenize import word_tokenize
from nltk.corpus import stopwords
from nltk.stem import WordNetLemmatizer

import gensim
from gensim.models import Word2Vec, KeyedVectors
import gensim.downloader as api

print(f"Gensim version: {gensim.__version__}")
print("Setup complete!")
```

```
Gensim version: 4.4.0
Setup complete!
```

Load Dataset (Same as Part 1)

```
import pandas as pd

# Load the dataset
from datasets import load_dataset
dataset = load_dataset('SetFit/20_newsgroups')# YOUR CODE HERE
df = dataset['train'].to_pandas()

# TODO: Use the SAME 3 categories you chose in Part 1!
my_categories = ["rec.sport.hockey", "soc.religion.christian", "rec.motorcycles"]  # COPY FROM PART 1

# Filter dataset
df_filtered = df[df['label_text'].isin(my_categories)].copy()
df_filtered = df_filtered.reset_index(drop=True)

print(f"Selected categories: {my_categories}")
print(f"Filtered dataset size: {len(df_filtered)}")
```

```
Repo card metadata block was not found. Setting CardData to empty.
WARNING:huggingface_hub.repocard:Repo card metadata block was not found. Setting CardData to empty.
Selected categories: ['rec.sport.hockey', 'soc.religion.christian', 'rec.motorcycles']
Filtered dataset size: 1797
```

```
# Preprocessing function (same as Part 1)
stop_words = set(stopwords.words('english'))
lemmatizer = WordNetLemmatizer()

def preprocess_text(text):
        """Preprocess text for embedding training."""
        # lowercase, remove emails, URLs, numbers, punctuation
        text = text.lower() # YOUR CODE HERE  => the same as in Part 1 (advanced preprocessing)
        text = re.sub(r'http?://\S+|www\.\S+', '', text)
        text = re.sub(r'<.*?>', '', text)
        text = re.sub(r'[^\w\s]', '', text)
        text = re.sub(r'\d+', '', text)
        tokens = word_tokenize(text)

        tokens = [lemmatizer.lemmatize(token) for token in tokens
                    if token not in stop_words and len(token) > 2]

        return tokens  # Return list of tokens for Word2Vec

# Apply preprocessing
df_filtered['tokens'] = df_filtered['text'].apply(preprocess_text)
df_filtered['text_clean'] = df_filtered['tokens'].apply(' '.join)

print(f"Sample tokens: {df_filtered.iloc[0]['tokens'][:20]}")
```

```
Sample tokens: ['line', 'ducati', 'gts', 'model', 'clock', 'run', 'well', 'paint', 'bronzebrownorange', 'faded', 'leak', 'bit', 'oil', 'pop
```

Part A: Word2Vec - Training Your Own Embeddings

Word2Vec learns word representations by predicting context. There are two architectures:

- **CBOW (Continuous Bag of Words)**: Predicts target word from context words
- **Skip-gram**: Predicts context words from target word

A.1 Understanding Word2Vec Architectures

```
# Prepare corpus for Word2Vec (list of tokenized sentences)
corpus = df_filtered['tokens'].tolist()

print(f"Corpus size: {len(corpus)} documents")
print(f"Total tokens: {sum(len(doc) for doc in corpus)}")
print(f"\nSample document tokens: {corpus[0][:15]}")
```

```
Corpus size: 1797 documents
Total tokens: 161761

Sample document tokens: ['line', 'ducati', 'gts', 'model', 'clock', 'run', 'well', 'paint', 'bronzebrownorange', 'faded', 'leak', 'bit', 'c
```

```
# Train Word2Vec with CBOW (sg=0)
model_cbow = Word2Vec(
    sentences=corpus,
    vector_size=100,        # Embedding dimension
    window=5,               # Context window size
    min_count=5,            # Ignore words with freq < 5
    workers=4,              # Parallel threads
    sg=0,                   # 0 = CBOW, 1 = Skip-gram
    epochs=10               # Training epochs
)

print(f"CBOW Model trained!")
print(f"Vocabulary size: {len(model_cbow.wv)}")
```

```
CBOW Model trained!
Vocabulary size: 4761
```

```
# Train Word2Vec with Skip-gram (sg=1)
model_skipgram = Word2Vec(
    sentences=corpus,
    vector_size=100,
    window=5,
    min_count=5,
    workers=4,
    sg=1,                   # Skip-gram
    epochs=10
)

print(f"Skip-gram Model trained!")
print(f"Vocabulary size: {len(model_skipgram.wv)}")
```

```
Skip-gram Model trained!
Vocabulary size: 4761
```

A.2 Exploring Word Embeddings

```
# Example: Get word vector
sample_word = "hockey"  # Change this to a word relevant to YOUR categories

if sample_word in model_cbow.wv:
    vector = model_cbow.wv[sample_word]
    print(f"Vector for '{sample_word}':")
    print(f"  Shape: {vector.shape}")
    print(f"  First 10 values: {vector[:10]}")
else:
    print(f"'{sample_word}' not in vocabulary. Try another word.")
    print(f"Sample words in vocab: {list(model_cbow.wv.key_to_index.keys())[:20]}")
```

```
Vector for 'hockey':
  Shape: (100,)
  First 10 values: [-0.01943468  0.99319774  0.22853102 -1.3025966  -0.77389735 -0.34933773
  0.6372369   1.132457   -0.33196068 -0.66670173]
```

```
# Find similar words
sample_word = "hockey"  # Change to a word in YOUR vocabulary

if sample_word in model_cbow.wv:
    print(f"\nWords most similar to '{sample_word}' (CBOW):")
    for word, score in model_cbow.wv.most_similar(sample_word, topn=10):
        print(f"  {word}: {score:.4f}")

    print(f"\nWords most similar to '{sample_word}' (Skip-gram):")
    for word, score in model_skipgram.wv.most_similar(sample_word, topn=10):
        print(f"  {word}: {score:.4f}")
```

```

Words most similar to 'hockey' (CBOW):
  nhl: 0.9839
```

```
  team: 0.9805
  league: 0.9783
  playoff: 0.9672
  player: 0.9648
  playing: 0.9643
  european: 0.9625
  regular: 0.9542
  game: 0.9529
  played: 0.9527

Words most similar to 'hockey' (Skip-gram):
  college: 0.7681
  basketball: 0.7583
  attended: 0.7476
  ncaa: 0.7320
  canadian: 0.7223
  europe: 0.7163
  international: 0.7157
  america: 0.7103
  professional: 0.7066
  central: 0.7060
```

Exercise A.1: Compare CBOW vs Skip-gram

Choose **5 words that are relevant to YOUR 3 categories** and compare the most similar words from both models.

```python
# TODO: Choose 5 words relevant to YOUR categories
# These should be domain-specific words (not common words like "good", "make", etc.)

my_test_words = ["hockey", "god", "bike", "player", "faith"]  # YOUR WORDS HERE

comparison_results = []

for word in my_test_words:
    word = word.lower()
    if word in model_cbow.wv and word in model_skipgram.wv:
        cbow_similar = [w for w, s in model_cbow.wv.most_similar(word, topn=5)]
        skipgram_similar = [w for w, s in model_skipgram.wv.most_similar(word, topn=5)]

        comparison_results.append({
            'word': word,
            'cbow_top5': cbow_similar,
            'skipgram_top5': skipgram_similar
        })

        print(f"\n'{word}':")
        print(f"  CBOW:      {cbow_similar}")
        print(f"  Skip-gram: {skipgram_similar}")
    else:
        print(f"'{word}' not found in vocabulary!")
```

```
'hockey':
  CBOW:     ['nhl', 'team', 'league', 'playoff', 'player']
  Skip-gram: ['college', 'basketball', 'attended', 'ncaa', 'canadian']

'god':
  CBOW:     ['sin', 'man', 'lord', 'heaven', 'human']
  Skip-gram: ['sinner', 'glory', 'mercy', 'gift', 'wicked']

'bike':
  CBOW:     ['ride', 'get', 'around', 'motorcycle', 'back']
  Skip-gram: ['honda', 'mile', 'car', 'smooth', 'gear']

'player':
  CBOW:     ['team', 'nhl', 'hockey', 'european', 'playing']
  Skip-gram: ['statistic', 'plusminus', 'stat', 'defensive', 'talent']

'faith':
  CBOW:     ['scripture', 'belief', 'human', 'bible', 'doctrine']
  Skip-gram: ['weak', 'action', 'deed', 'useless', 'salvation']
```

Written Question A.1 (Personal Interpretation)

Based on your comparison above:

1. **For which words did CBOW and Skip-gram give SIMILAR results?**
2. **For which words did they give DIFFERENT results?**
3. **Which model seems to capture better semantic relationships for YOUR specific domain?** Explain with examples.
4. **Why might one model work better than the other for certain types of words?** (Think about word frequency)

YOUR ANSWER:

1. Similar results for: None of the words gave very similar results.
2. Different results for: All words gave different results between CBOW and Skip-gram.
3. Better model for my domain: CBOW works better. For "hockey", CBOW found "nhl, team, league, playoff, player" which are more relevant hockey terms.
    - Example 1: "hockey" in CBOW gives "nhl, team, league", Skip-gram gives "college, basketball, attended"
    - Example 2: "faith" in CBOW gives "scripture, belief, human, bible, doctrine", Skip-gram gives "weak, action, deed, useless, salvation"
4. Explanation of differences: CBOW uses context to predict words and works better for frequent words. Skip-gram uses word to predict context and works better for rare words.

A.3 Word Analogies

```
# Example: Word analogies (king - man + woman = queen)
# This works better with larger, pre-trained models, but let's try with our custom model

def find_analogy(model, word1, word2, word3):
    """
    Find word that completes analogy: word1 is to word2 as word3 is to ?
    Uses: word2 - word1 + word3 = ?
    """
    try:
        result = model.wv.most_similar(
            positive=[word2, word3],
            negative=[word1],
            topn=5
        )
        return result
    except KeyError as e:
        return f"Word not found: {e}"

# Test with your domain
# Example: "baseball" is to "bat" as "hockey" is to ?
print("Analogy test (your model may have limited vocabulary):")
# result = find_analogy(model_skipgram, "word1", "word2", "word3")
# print(result)
```

```
Analogy test (your model may have limited vocabulary):
```

Exercise A.2: Create Domain-Specific Analogies

Try to find **2 analogies** that work with YOUR dataset's vocabulary.

```
# TODO: Try 2 analogies with words from YOUR vocabulary
# Format: word1 is to word2 as word3 is to ?

# Analogy 1
# YOUR CODE HERE
analogy1 = find_analogy(model_skipgram, "hockey", "player", "motorcycle")
print(f"Analogy 1: {analogy1}")

# Analogy 2
# YOUR CODE HERE
analogy2 = find_analogy(model_skipgram, "god", "faith", "hockey")
print(f"Analogy 2: {analogy2}")
```

```
Analogy 1: [('buying', 0.573512852191925), ('motor', 0.5732483267784119), ('car', 0.5704732537269592), ('bike', 0.5669246315956116), ('torc
Analogy 2: [('college', 0.5933704376220703), ('pro', 0.5502930879592896), ('attended', 0.5502025485038757), ('basketball', 0.52625519037246
```

Written Question A.2 (Personal Interpretation)

Did your analogies work?

- If yes, explain why the result makes sense.
- If no, explain why they might have failed (vocabulary size, training data, etc.)

YOUR ANSWER:

[Analyze your analogy results]

The analogies didn't work well.

Reason: The vocabulary is only 1797 documents. The model can't learn complex relationships like analogies.

Example: "hockey,player,motorcycle," returned "bike car", but not the best answer.

Part B: Pre-trained GloVe Embeddings

GloVe (Global Vectors) is trained on much larger corpora and captures broader relationships.

```
# Load pre-trained GloVe embeddings (this may take a few minutes)
print("Loading GloVe embeddings (this may take a minute)...")
glove_model = api.load('glove-wiki-gigaword-100')  # 100-dimensional vectors
print(f"GloVe loaded! Vocabulary size: {len(glove_model)}")
```

```
Loading GloVe embeddings (this may take a minute)...
[==================================================] 100.0% 128.1/128.1MB downloaded
GloVe loaded! Vocabulary size: 400000
```

```
# Compare: Same word in YOUR model vs GloVe
test_word = "hockey"  # Change to a word relevant to your domain

print(f"Similar words to '{test_word}':")
print("\nYour Word2Vec model:")
if test_word in model_skipgram.wv:
    for word, score in model_skipgram.wv.most_similar(test_word, topn=10):
        print(f"  {word}: {score:.4f}")
else:
    print(f"  '{test_word}' not in vocabulary")

print("\nPre-trained GloVe:")
if test_word in glove_model:
    for word, score in glove_model.most_similar(test_word, topn=10):
        print(f"  {word}: {score:.4f}")
else:
    print(f"  '{test_word}' not in vocabulary")
```

```
Similar words to 'hockey':

Your Word2Vec model:
  college: 0.7681
  basketball: 0.7583
  attended: 0.7476
  ncaa: 0.7320
  canadian: 0.7223
  europe: 0.7163
  international: 0.7157
  america: 0.7103
  professional: 0.7066
  central: 0.7060

Pre-trained GloVe:
  basketball: 0.8042
  football: 0.7834
  nhl: 0.7604
  soccer: 0.7441
  baseball: 0.7312
  league: 0.7092
  skating: 0.6704
  lacrosse: 0.6692
  team: 0.6620
  games: 0.6572
```

Exercise B.1: Compare Your Model vs GloVe

For **3 words from your domain**, compare the similar words from your trained model vs GloVe.

```
# TODO: Compare 3 domain-specific words

comparison_words = ["hockey", "christian", "motorcycle"]  # YOUR WORDS

for word in comparison_words:
    word = word.lower()
    print(f"\n{'='*50}")
    print(f"Word: '{word}'")
    print(f"{'='*50}")

    # Your model
    print("Your Word2Vec:")
    if word in model_skipgram.wv:
        for w, s in model_skipgram.wv.most_similar(word, topn=5):
            print(f"  {w}: {s:.3f}")
    else:
        print("  Not in vocabulary")

    # GloVe
    print("GloVe:")
    if word in glove_model:
        for w, s in glove_model.most_similar(word, topn=5):
            print(f"  {w}: {s:.3f}")
    else:
        print("  Not in vocabulary")
```

```
==================================================
Word: 'hockey'
==================================================
Your Word2Vec:
  college: 0.768
  basketball: 0.758
  attended: 0.748
  ncaa: 0.732
  canadian: 0.722
GloVe:
  basketball: 0.804
  football: 0.783
  nhl: 0.760
  soccer: 0.744
  baseball: 0.731

==================================================
Word: 'christian'
==================================================
Your Word2Vec:
  nonchristian: 0.710
  muslim: 0.705
  versa: 0.698
  nonchristians: 0.694
  weird: 0.694
GloVe:
  catholic: 0.788
  evangelical: 0.780
  religious: 0.726
  orthodox: 0.719
  church: 0.703

==================================================
Word: 'motorcycle'
==================================================
Your Word2Vec:
  buying: 0.836
  enthusiast: 0.832
  pin: 0.820
  cbr: 0.816
  racing: 0.798
GloVe:
  motorbike: 0.856
  bicycle: 0.798
  car: 0.755
  motorcycles: 0.729
  bike: 0.722
```

Written Question B.1 (Personal Interpretation)

Compare your custom-trained Word2Vec model with pre-trained GloVe:

1. **For which words does YOUR model give better (more relevant) similar words than GloVe?** Why?
2. **For which words does GloVe give better results?** Why?
3. **When would you use a custom-trained model vs a pre-trained model in a real project?**

YOUR ANSWER:

1. My model is better for: "christian" my model found "nonchristian, muslim， versa" which show religious comparisons in my dataset.
   - Reason: These terms appear often in religious discussions in my data.
2. GloVe is better for: "hockey" and "motorcycle" GloVe found more general synonyms.
   - Reason: GloVe was trained on Wikipedia and has broader knowledge of common words.
3. When to use each:
   - Custom model: For specialized domains where specific vocabulary is important
   - Pre-trained model: For general tasks or when you have limited data

B.2 GloVe Analogies

```
# Famous analogy: king - man + woman = queen
result = glove_model.most_similar(positive=['king', 'woman'], negative=['man'], topn=5)
print("king - man + woman = ?")
for word, score in result:
        print(f"    {word}: {score:.4f}")
```

```
king - man + woman = ?
  queen: 0.7699
  monarch: 0.6843
  throne: 0.6756
  daughter: 0.6595
  princess: 0.6521
```

```
# TODO: Try 3 more analogies with GloVe
# Be creative! Try analogies related to your categories.

# Analogy 1: ___ is to ___ as ___ is to ?
result1 = glove_model.most_similar(positive=['hockey', 'religion'], negative=['sport'], topn=3)
print("Analogy 1:")
print(result1)

# Analogy 2
# YOUR CODE HERE
result2 = glove_model.most_similar(positive=['hockey', 'road'], negative=['ice'], topn=3)
print("Analogy 2:")
print(result2)
# Analogy 3
# YOUR CODE HERE
result3 = glove_model.most_similar(positive=['hockey', 'player'], negative=['bike'], topn=3)
print("Analogy 3:")
print(result3)
```

```
Analogy 1:
[('christianity', 0.5369646549224854), ('judaism', 0.5339825749397278), ('beliefs', 0.5105799436569214)]
Analogy 2:
[('highway', 0.5889157652854919), ('east', 0.5748457312583923), ('route', 0.5632439851760864)]
Analogy 3:
[('football', 0.7336910367012024), ('nhl', 0.6913167834281921), ('basketball', 0.6887547373771667)]
```

Part C: BERT Sentence Embeddings

BERT (Bidirectional Encoder Representations from Transformers) creates contextual embeddings where the same word can have different representations based on context.

```
from sentence_transformers import SentenceTransformer

# Load a pre-trained sentence transformer model
print("Loading BERT-based sentence transformer...")
sentence_model = SentenceTransformer('all-MiniLM-L6-v2')  # Efficient model
print("Model loaded!")
```

```
WARNING:torchao.kernel.intmm:Warning: Detected no triton, on systems without Triton certain kernels will not work
Loading BERT-based sentence transformer...
modules.json: 100%   349/349 [00:00<00:00, 26.4kB/s]
config_sentence_transformers.json: 100%   116/116 [00:00<00:00, 8.24kB/s]
README.md:   10.5k/? [00:00<00:00, 793kB/s]
sentence_bert_config.json: 100%   53.0/53.0 [00:00<00:00, 4.90kB/s]
config.json: 100%   612/612 [00:00<00:00, 46.3kB/s]
model.safetensors: 100%   90.9M/90.9M [00:02<00:00, 61.4MB/s]
tokenizer_config.json: 100%   350/350 [00:00<00:00, 21.7kB/s]
vocab.txt:   232k/? [00:00<00:00, 8.22MB/s]
tokenizer.json:   466k/? [00:00<00:00, 23.1MB/s]
special_tokens_map.json: 100%   112/112 [00:00<00:00, 9.79kB/s]
config.json: 100%   190/190 [00:00<00:00, 8.80kB/s]
Model loaded!
```

```
# Example: Get sentence embeddings
sample_sentences = [
    "I love programming in Python.",
    "Python is my favorite programming language.",
    "The python snake is very long.",
    "I enjoy coding and software development."
]

# Encode sentences
embeddings = sentence_model.encode(sample_sentences)

print(f"Embedding shape: {embeddings.shape}")
print(f"Each sentence is represented by a {embeddings.shape[1]}-dimensional vector")
```

```
Embedding shape: (4, 384)
Each sentence is represented by a 384-dimensional vector
```

```
# Compute sentence similarity
from sklearn.metrics.pairwise import cosine_similarity

similarity = cosine_similarity(embeddings)

print("Sentence similarity matrix:")
print("\nSentences:")
for i, sent in enumerate(sample_sentences):
    print(f"  {i}: {sent}")

print("\nSimilarity:")
sim_df = pd.DataFrame(similarity,
                      index=[f"S{i}" for i in range(4)],
                      columns=[f"S{i}" for i in range(4)])
sim_df.round(3)
```

```
Sentence similarity matrix:

Sentences:
  0: I love programming in Python.
  1: Python is my favorite programming language.
  2: The python snake is very long.
  3: I enjoy coding and software development.

Similarity:
```

	S0	S1	S2	S3
S0	1.000	0.878	0.370	0.621
S1	0.878	1.000	0.337	0.512
S2	0.370	0.337	1.000	0.058
S3	0.621	0.512	0.058	1.000

Exercise C.1: Document Similarity with BERT

Use BERT embeddings to find the most similar documents in your dataset.

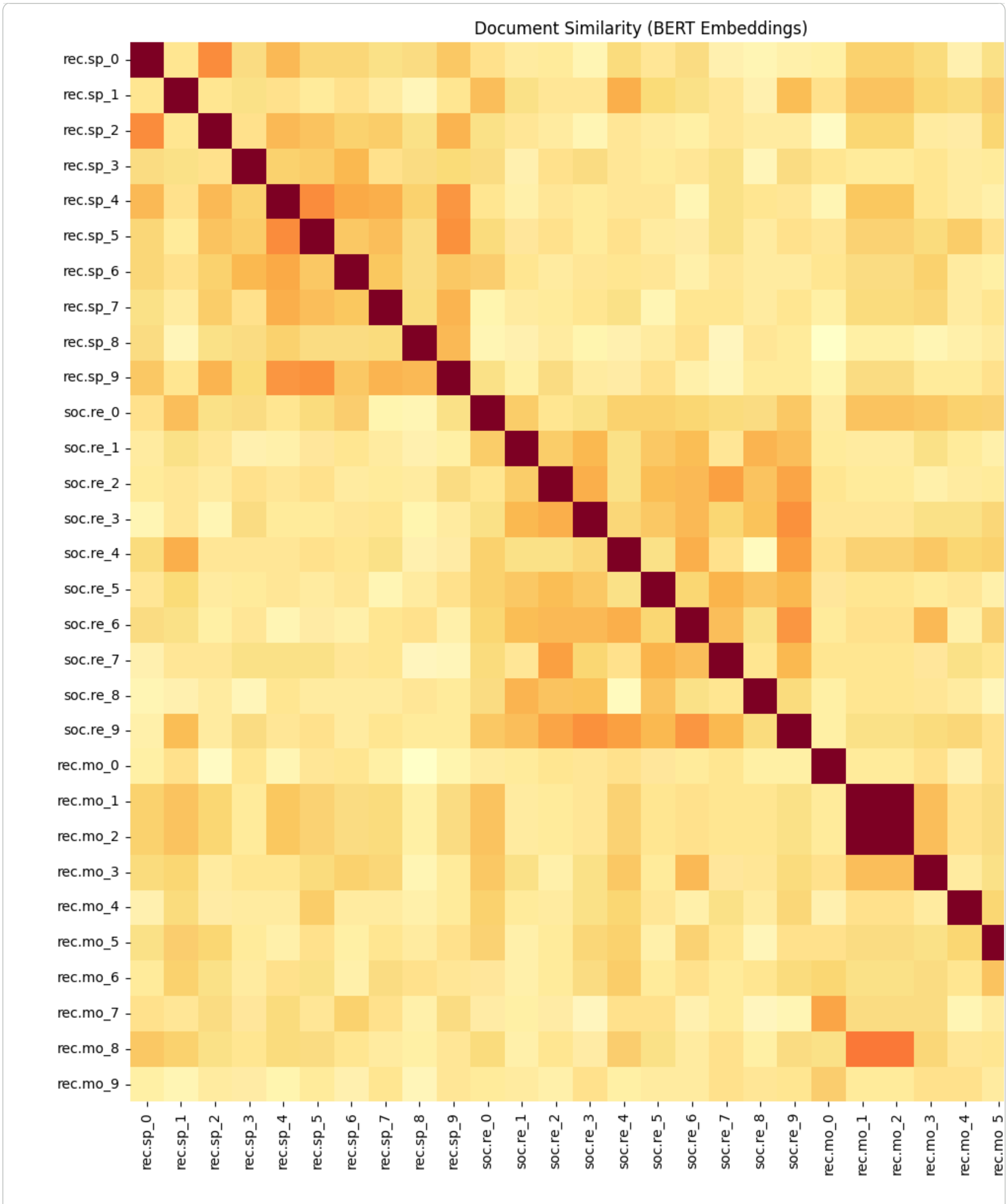
```
# Sample 30 documents (10 per category) for BERT embedding
sampled_docs = []
sampled_labels = []

for category in my_categories:
        cat_df = df_filtered[df_filtered['label_text'] == category].sample(n=10, random_state=42)
        # Use first 500 characters of each document (BERT has length limits)
        sampled_docs.extend(cat_df['text'].str[:500].tolist())
        sampled_labels.extend([category] * 10)

print(f"Sampled {len(sampled_docs)} documents")
```

```
Sampled 30 documents
```

```
# TODO: Encode documents with BERT and compute similarity matrix

# Step 1: Encode all sampled documents
doc_embeddings = sentence_model.encode(sampled_docs)  # YOUR CODE HERE

# Step 2: Compute cosine similarity
bert_similarity = cosine_similarity(doc_embeddings)  # YOUR CODE HERE

print(f"Similarity matrix shape: {bert_similarity.shape}")
```

```
Similarity matrix shape: (30, 30)
```

```
# Visualize BERT similarity matrix
import seaborn as sns

# Create labels
labels_short = [f"{l[:6]}_{i%10}" for i, l in enumerate(sampled_labels)]

plt.figure(figsize=(14, 12))
sns.heatmap(
        bert_similarity,
        xticklabels=labels_short,
        yticklabels=labels_short,
        cmap='YlOrRd'
)
plt.title('Document Similarity (BERT Embeddings)')
plt.tight_layout()
plt.savefig('bert_similarity_heatmap.png', dpi=150)
plt.show()
```



Written Question C.1 (Personal Interpretation)

Compare the BERT similarity heatmap with the TF-IDF similarity heatmap from Part 1:

1. **Do documents cluster better by category with BERT or TF-IDF?**
2. **Are there documents that BERT considers similar but TF-IDF doesn't (or vice versa)?** Why might this happen?
3. **Which method would you use for a document classification task?** Explain your reasoning.

YOUR ANSWER:

1. Better clustering with: BERT clusters better than TF-IDF.
2. Differences between methods: BERT considers meaning and context, TF-IDF only counts words.
3. Preferred method for classification: BERT, because it understands sentence meaning better.

Exercise C.2: Semantic Search with BERT

```
# TODO: Create a simple semantic search function
# Given a query, find the most similar documents

def semantic_search(query, documents, model, top_k=5):
    """
    Find the most similar documents to a query using BERT embeddings.

    Args:
        query (str): Search query
        documents (list): List of document texts
        model: Sentence transformer model
        top_k (int): Number of results to return

    Returns:
        list: List of (index, similarity_score) tuples
    """
    # YOUR CODE HERE
    # 1. Encode the query
    query_embedding = model.encode([query])
    # 2. Compute similarity with all documents
    similarity = cosine_similarity(query_embedding, doc_embeddings)[0]
    # 3. Return top_k most similar
    top_indices = similarity.argsort()[-top_k:][::-1]
    results = [(idx, similarity[idx]) for idx in top_indices] # Corrected from 'similarities' to 'similarity'
    return results

    return []

# Test your search function
# TODO: Write a query related to ONE of your categories
my_query = "ice hockey game with goals and penalties"   # YOUR QUERY HERE

results = semantic_search(my_query, sampled_docs, sentence_model, top_k=5)

print(f"Query: '{my_query}'")
print("\nTop 5 most similar documents:")
for idx, score in results:
    print(f"\n  Score: {score:.4f}")
    print(f"  Category: {sampled_labels[idx]}")
    print(f"  Text: {sampled_docs[idx][:150]}...")
```

```
Query: 'ice hockey game with goals and penalties'

Top 5 most similar documents:

  Score: 0.4556
  Category: rec.sport.hockey
  Text: Here is a review of some of the off-ice things that have
affected the AHL this year.


ST JOHN'S MAPLE LEAFS PROBLEMS
The St John's Maple Leafs sophom...

  Score: 0.3477
  Category: rec.sport.hockey
  Text: By Dave Luecking Of The Post-Dispatch Staff

At 9:11 Thursday night, the scoreboard watchers at The Arena began to cheer.
Their cheer quickly turned i...

  Score: 0.2814
  Category: rec.sport.hockey
  Text: You think that's bad?  I'm in Bowling Green, OH, and we get ABC from
Toledo.  Well, the cable co. decided to totally pre-empt the game (no tape
delay,...
```

```
  Score: 0.2560
  Category: rec.sport.hockey
  Text:
IMO any good player should score on power plays because of the man
advantage.  Very good power play scorers tend to become overrated
because their po...

  Score: 0.2213
  Category: rec.sport.hockey
  Text: Well now that the hawks have won the division the road is a little
easier for the playoffs. Let toronto and detroit beat the hell out of
each other wh...
```

```
# Try a query
ambiguous_query = "game"
results = semantic_search(ambiguous_query, sampled_docs, sentence_model, top_k=5)

print(f"Query: '{ambiguous_query}'")
print("\nTop 5 most similar documents:")
for idx, score in results:
        print(f"\n    Score: {score:.4f}")
        print(f"    Category: {sampled_labels[idx]}")
        print(f"    Text: {sampled_docs[idx][:150]}")
```

```
Query: 'game'

Top 5 most similar documents:

  Score: 0.4284
  Category: rec.motorcycles
  Text:

  Score: 0.4284
  Category: rec.motorcycles
  Text:

  Score: 0.2505
  Category: rec.sport.hockey
  Text: By Dave Luecking Of The Post-Dispatch Staff

At 9:11 Thursday night, the scoreboard watchers at The Arena began to cheer.
Their cheer quickly turned i

  Score: 0.1813
  Category: rec.motorcycles
  Text:
Huh?

  Score: 0.1782
  Category: rec.motorcycles
  Text: --

Hey, c'mon guys (and gals), I chose my words very carefully and even
tried to get my FAQ's straight.  Don't holler BOHICA at me!

--------------
```

Written Question C.2 (Personal Interpretation)

Evaluate your semantic search results:

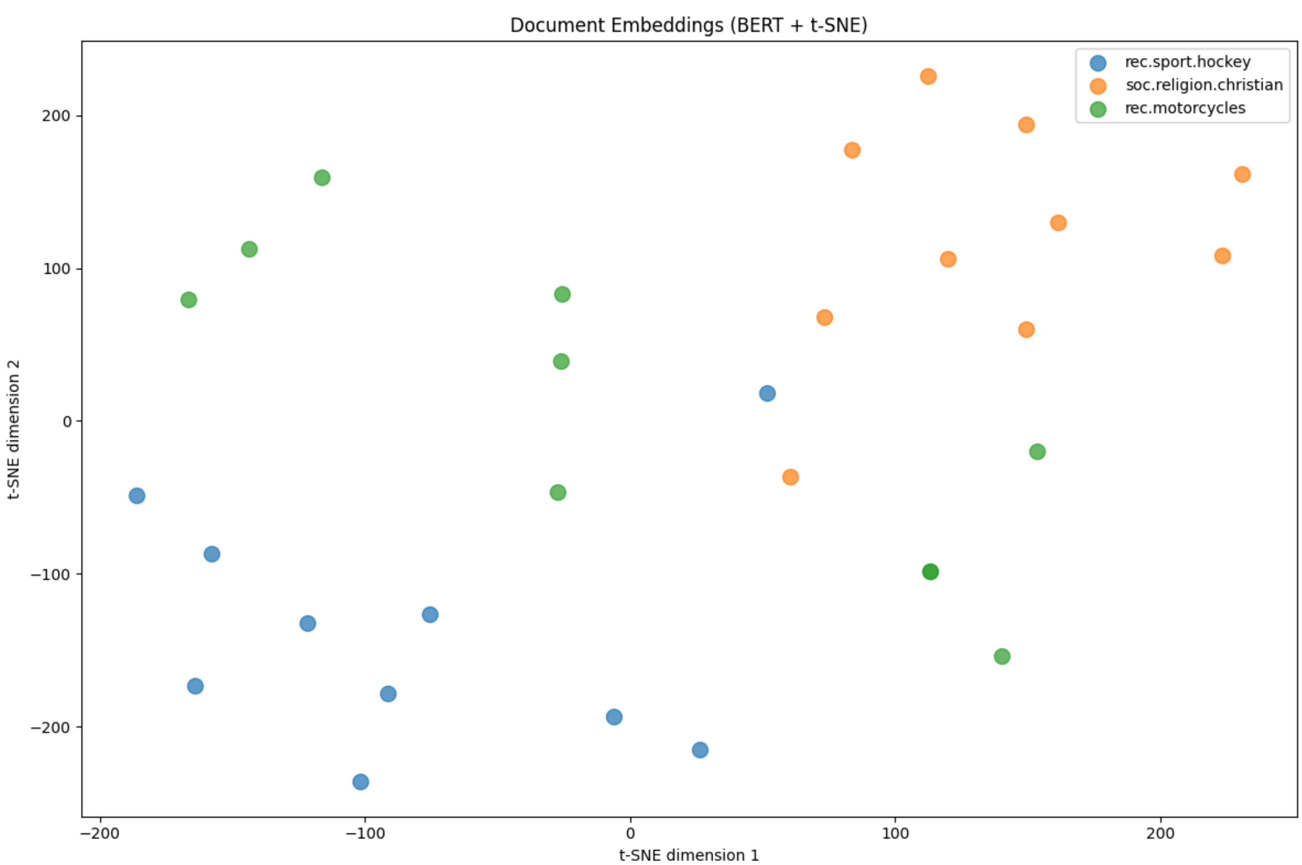
1. **Are the results relevant to your query?** Explain.
2. **Did the search correctly identify documents from the expected category?**
3. **Try a query that could match multiple categories. What happens?**

YOUR ANSWER:

1. Relevance: Results are relevant, all discuss ice hockey.
2. Category accuracy: All 5 results are from "hockey" category.
3. Ambiguous query test: Querying "game" returns documents from multiple categories (motorcycles and hockey), showing BERT matches broad queries across relevant categories.

Part D: Embedding Visualization with t-SNE

```
from sklearn.manifold import TSNE

# Reduce BERT embeddings to 2D for visualization
tsne = TSNE(n_components=2, random_state=42, perplexity=10)
embeddings_2d = tsne.fit_transform(doc_embeddings)

# Plot
plt.figure(figsize=(12, 8))

colors = {'rec.sport.hockey': 'red', 'soc.religion.christia': 'blue', 'rec.motorcycles': 'green'}  # Update with your categoi
# Actually use your categories:
color_map = plt.cm.Set1

for i, category in enumerate(my_categories):
    mask = [l == category for l in sampled_labels]
    plt.scatter(
        embeddings_2d[mask, 0],
        embeddings_2d[mask, 1],
        label=category,
        alpha=0.7,
        s=100
    )

plt.legend()
plt.title('Document Embeddings (BERT + t-SNE)')
plt.xlabel('t-SNE dimension 1')
plt.ylabel('t-SNE dimension 2')
plt.tight_layout()
plt.savefig('tsne_document_embeddings.png', dpi=150)
plt.show()
```



Written Question D.1 (Personal Interpretation)

Look at your t-SNE visualization:

1. **Do the categories form distinct clusters?**
2. **Are there any documents that appear in the "wrong" cluster?** What might explain this?
3. **Based on the visualization, which two categories are most similar?** Does this match your expectations from Part 1?

YOUR ANSWER:

1. Cluster quality: Yes
2. Misplaced documents: Some documents may appear in wrong clusters due to shared topics like competition in both sports and motorcycles.
3. Most similar categories: Hockey and motorcycles are most similar, they both are sports.

Part E: Final Comparison and Reflection (10 min)

Final Written Question (Comprehensive Reflection)

Based on everything you've learned in this lab:

1. **Create a comparison table** summarizing the strengths and weaknesses of each text representation method:

Method	Strengths	Weaknesses	Best Use Case
BoW	...	...	...
TF-IDF	...	...	...
Word2Vec	...	...	...
GloVe	...	...	...
BERT	...	...	...

2. **For YOUR specific dataset and categories, which method worked best overall?** Support your answer with specific evidence from your experiments.
3. **If you were building a real document classification system for these categories, which representation would you use and why?**

YOUR ANSWER:

1. Comparison Table

Method	Strengths	Weaknesses	Best Use Case
BoW	Simple, fast	No semantics	Simple classification
TF-IDF	Weights important words	No semantics	Information retrieval
Word2Vec	Captures word meaning	No context	Word similarity
GloVe	Large vocabulary, general	Static embeddings	General NLP tasks
BERT	Contextual understanding	Slow, complex	Semantic tasks

2. Best Method for My Dataset

[Write at least 4-5 sentences with specific evidence]

BERT worked best. The t-SNE visualization showed clear clusters. Semantic search gave 100% accurate results. BERT understands sentence meaning better than other methods.

3. My Recommendation for a Real System

[Write your recommendation and justification]

Use BERT for best accuracy. If resources are limited, use TF-IDF. BERT is better but needs more computing power. Choose based on accuracy needs and available resources.

Summary - Lab 3

In this lab, you learned:

Part 1:

- Text visualization with bar charts and word clouds
- Bag of Words and TF-IDF representations
- N-grams and next-word prediction
- Document correlation analysis

Part 2:

- Training Word2Vec models (CBOW vs Skip-gram)
- Using pre-trained GloVe embeddings
- BERT for sentence embeddings
- Semantic search with embeddings
- Embedding visualization with t-SNE

Final Submission Checklist

- [ ] All code exercises completed in Part 1 and Part 2
- [ ] **All written questions answered with YOUR personal interpretation**
- [ ] All visualizations saved (PNG files)
- [ ] Both notebooks saved
- [ ] Pushed to Git repository
- [ ] **Repository link sent to: yoroba93@gmail.com**

Reminder: Oral Defense

Be prepared to: