DSA4213 Assignment 1: Word Embeddings

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1. Data

1.1 Corpus Introduction

For this assignment, I use the **Corpus of Singapore English Messages (CoSEM)** as my training data (Gonzales et al. 2023). With almost 7 million words in total, this corpus contains a large collection of online text messages, reflecting contemporary Singaporean English

(Singlish). By training word embedding models on this corpus, we might be able to discover interesting local colloquialisms and conversational syntax.

1.2 Data Preprocessing

The raw corpus consists of 1385 individual text files, each file contains many lines of messages with private information being anonymized. For example,

```
<<COSEM:21DX12-5712-22SGCHMCK-2021>>    Tru gamers
<<COSEM:21DX12-5713-22SGCHMBL-2021>>    NM/M/CH/22 r u asleep
<<COSEM:21DX12-5714-22SGCHMBL-2021>>    {{URL}}
```

To make the corpus ready for training, a series of preprocessing steps are performed:

1. **Consolidation**: All text files are merged into a single file, `processed_corpus.txt`.
2. **Cleaning**: COSEM IDs, URLs, and all anonymized tags such as `<media omitted>` and `{email}` are all removed.
3. **Standardization**: All text is converted to lowercase, and only alphanumeric characters and spaces are retained (words are separated by exactly a single space).

After preprocessing and removing empty messages, we have a total of:

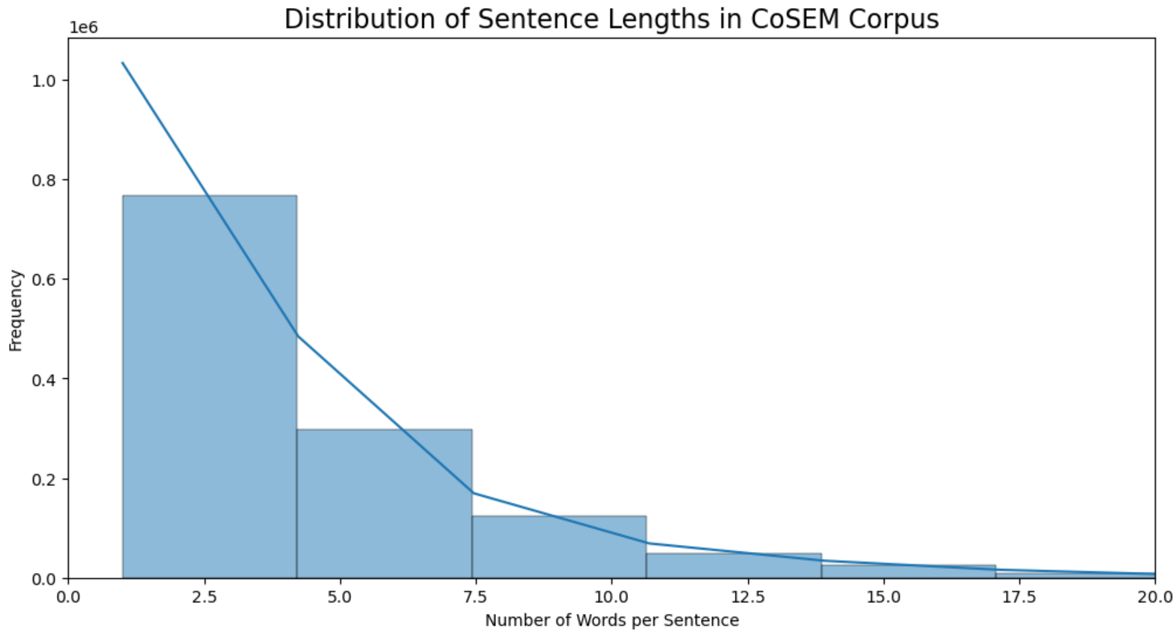
- 1,288,214 sentences
- 6,236,854 words
- 127,984 unique words

1.3 Exploratory Data Analysis

Some visualizations are created to understand the corpus's characteristics.

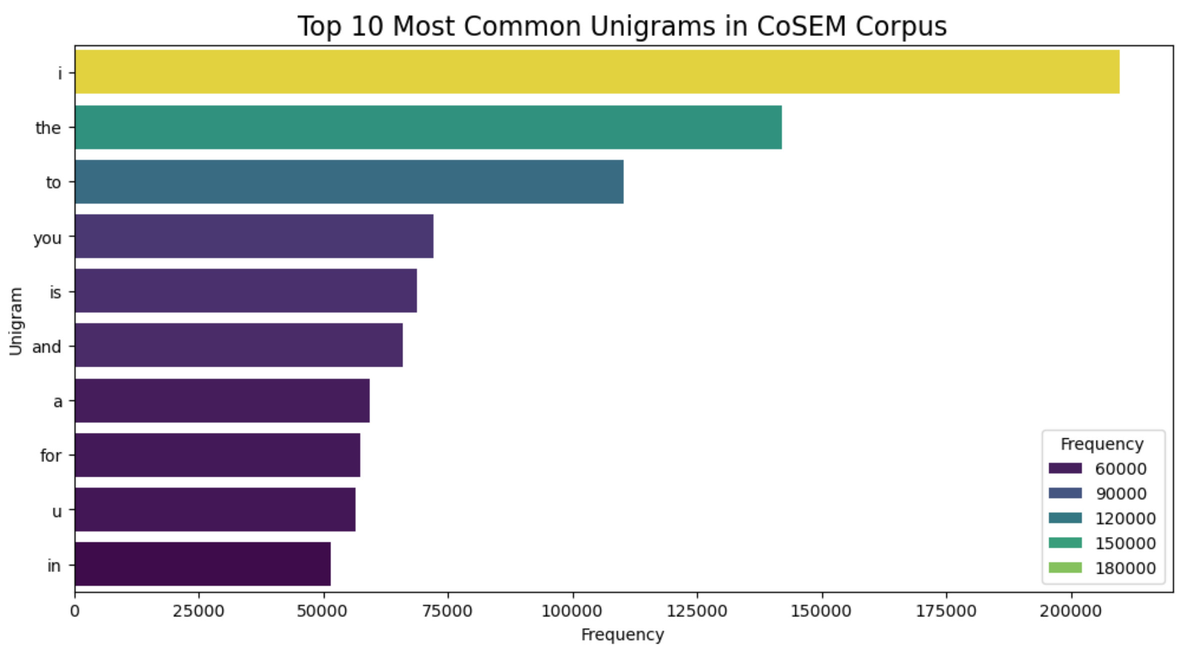
Sentence Length Distribution

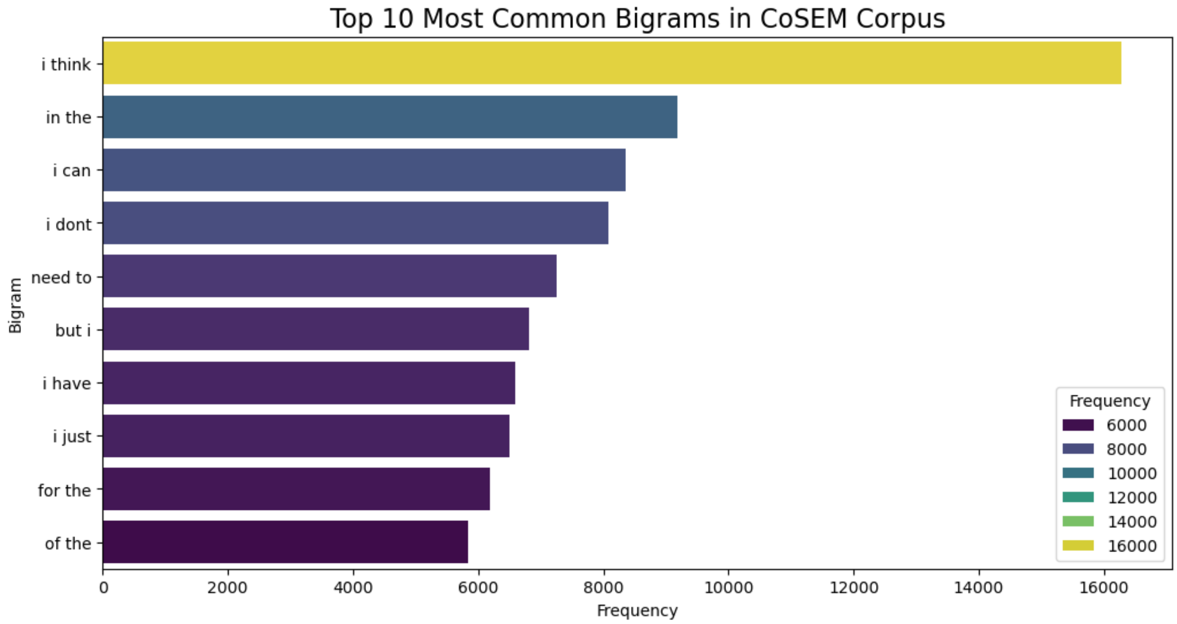
The messages are predominantly short, with most containing fewer than 10 words.



Unigram and Bigram Frequencies

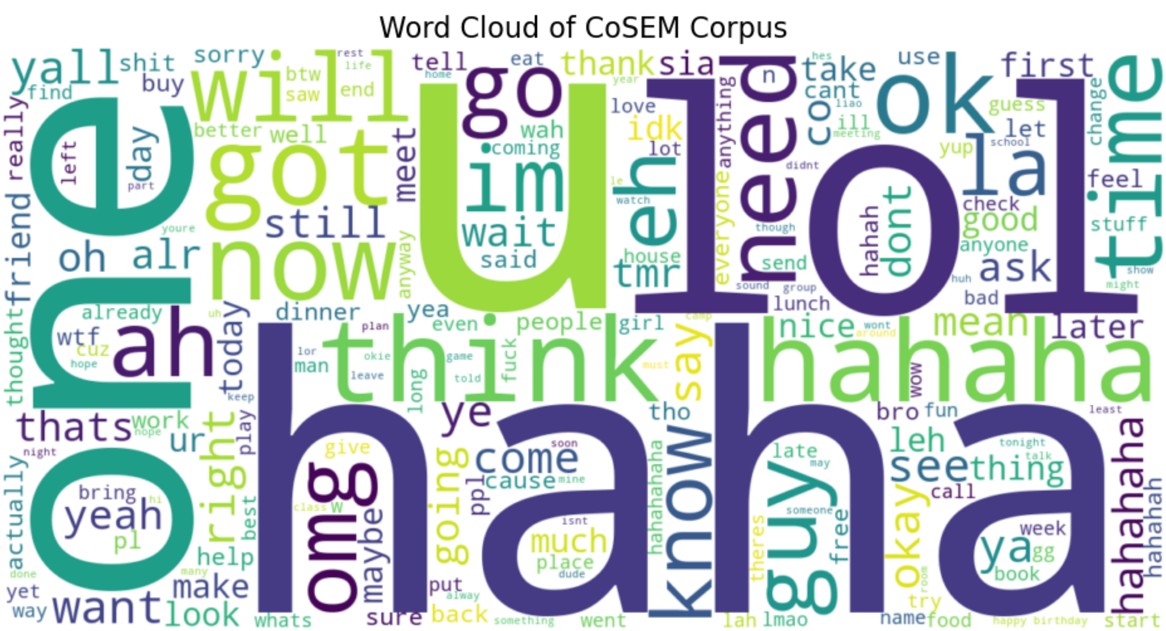
The most common unigrams (single words) and bigrams (two-word phrases) highlight the conversational and localized nature of the corpus.





Word Cloud

The word cloud can also provide a visual summary of the most frequent terms in the corpus, highlighting the informal nature of online text messages in the CoSEM corpus.



2. Models

2.1 Shared Hyperparameters

To ensure a fair comparison between the models later, the following core hyperparameters are kept consistent across all models:

Parameter	Skip-gram	SPPMI-SVD	GloVe	Description
Vector Size	50	50	50	Dimensionality of each word embedding
Window Size	5	5	5	Context window size
Minimum Vocabulary Count	10	10	10	Minimum word frequency to be included in vocabulary
Maximum Iterations	15	-	15	Maximum training iterations
Negative Samples	5	5	-	Number of negative samples for training

Note: With the minimum word frequency set to 10, the final vocabulary size for all models is reduced to 19,121 words.

2.2 Word2Vec (Skip-gram)

The Skip-gram model is a predictive model that learns word embeddings by trying to predict the context words surrounding a given center word using a neural network (Mikolov, Chen, et al. 2013).

The model is trained using the `gensim` library (Radim and Petr 2011), with negative sampling for efficient training (Mikolov, Sutskever, et al. 2013). Other than the shared hyperparameters mentioned earlier, the following default hyperparameters were used for the Skip-gram model:

Parameter	Value	Description
ns_exponent	0.75	Exponent for negative sampling distribution
alpha	0.025	Initial learning rate
min_alpha	0.0001	Minimum learning rate as learning rate linearly drops during training

2.3 SPPMI-SVD

This is a count-based method that operates on a co-occurrence matrix. It can be shown that training Word2Vec Skip-gram model with k negative samples is equivalent to factorizing the shifted point-wise mutual information matrix (Levy and Goldberg 2014). The matrix M can be defined as:

$$M_{ij} = \mathbf{w}_i \cdot \mathbf{c}_j = PMI(i,j) - \log k = \log\left(\frac{P(i,j)}{P(i)P(j)}\right) - \log k$$

With **Shifted Positive Pointwise Mutual Information (SPPMI)**, we actually modify $M_{ij} = \max(0, PMI(i,j) - \log k)$ to ensure non-negativity. Then **Singular Value Decomposition (SVD)** is used to factorize $M = U\Sigma V^T = (U\Sigma^{1/2})(\Sigma^{1/2}V^T)$. $(U\Sigma^{1/2})$ is used to obtain the word embeddings where we only use the top singular values and corresponding singular vectors from U and $\Sigma^{1/2}$ (50 in our case).

This algorithm is implemented using standard Python and `scipy` for efficient SVD computation.

2.4 GloVe

GloVe (Global Vectors) is another count-based method that operates on a co-occurrence matrix (Pennington, Socher, and Manning 2014). Its objective function is to learn vectors such that their dot product equals the logarithm of their co-occurrence probability $w_i \cdot w_j = \log P(w_i|w_j)$ by minimizing a weighted least squares objective that captures the ratios of co-occurrence probabilities $J = \sum_{i,j} f(X_{ij}) \cdot (\mathbf{w}_i^T \tilde{\mathbf{w}}_j + b_i + \tilde{b}_j - \log X_{ij})^2$ where X_{ij} is the co-occurrence count, and $f(x) = (x/c)^\alpha$ if $x < c$ and 1 otherwise.

This model is trained using the official GloVe implementation from Stanford NLP Group (in C programming language) with the hyperparameters $c = 10$, and $\alpha = 0.75$.

3. Evaluation

3.1 Nearest Neighbors Analysis

In this section, we will present the top 5 nearest neighbors for a curated list of common Singlish words for each of the three models. The meaning of each Singlish word will also be provided for better understanding, with references from (klingonpigeon 2024).

3.1.1 kiasu

> scared of losing out and being uncompetitive with others; selfish; overly-competitive to the point of stepping over others

None of the models display the closest synonyms to `kiasu` as `selfish` or `competitive`, but their closest words do show a negative connotation.

	Rank 1	Rank 2	Rank 3	Rank 4	Rank 5
Skip-gram	frustrating	agitated	enthu	misleading	distracting
SPPMI-SVD	simp	irritating	racist	anal	unlucky
GloVe	opponents	pressing	gathered	faulty	mutually

3.1.2 chope

> to reserve; to 'call dibs' on, especially a table or seat. It is usually customary accompany this by leaving a small personal object behind as a marker of reservation, such as a packet of tissue paper.

Skip-gram display the closest synonym to `chope` as `reserve` (although not ranked 1), while SPPMI-SVD and GloVe display objects that are usually associated with the act of `chope`ing, such as `seat`.

	Rank 1	Rank 2	Rank 3	Rank 4	Rank 5
Skip-gram	kope	reserve	w8	collate	kup
SPPMI-SVD	seated	seat	studio	clubroom	aircon
GloVe	seat	search	review	compile	google

3.1.3 paiseh

> embarrassed; shy; ashamed; sorry

All models recognize the emotional weight of `paiseh`, and display similar words with apologetic connotations.

	Rank 1	Rank 2	Rank 3	Rank 4	Rank 5
Skip-gram	sorz	sorry	sry	soz	psps
SPPMI-SVD	soz	sorz	ltr	dunnid	oops
GloVe	lambat	sorz	soz	sry	opps

3.1.4 sian

boring; tiresome; insipid

All models displays the closest synonyms to `sian` as `shag` (which is another local slang term for feeling bored or tired). Other related words with a similar sentiment (tiring) are also shown.

	Rank 1	Rank 2	Rank 3	Rank 4	Rank 5
Skip-gram	sianz	shag	siann	sadz	yalo
SPPMI-SVD	dam	shag	scary	damn	wah
GloVe	shag	sia	damn	wah	scared

3.1.5 dabao

(of food) to take-away; to order to go

Skip-gram and GloVe display the closest synonym to `dabao` as `dapao` (which is a variation in spelling). Similar to the example of `chope` above, SPPMI-SVD displays words that are usually associated with the act of `dabao`ing instead of synonyms.

	Rank 1	Rank 2	Rank 3	Rank 4	Rank 5
Skip-gram	dapao	tabao	tapao	subway	cook
SPPMI-SVD	eating	hwangs	eat	kopitiam	banmian
GloVe	dapao	groceries	buy	prepare	fetch

3.2 Word Analogy Analysis

This extends the previous section by experimenting with word analogies using vector operations. We will find the most similar words `d` for each analogy `a - b = c - d`.

Although there are many possible answers besides the `Expected` ones and the sample set is small, SPPMI-SVD gives pretty good results compared to the other models, although none of them gives satisfactory answers for all 5 rows.

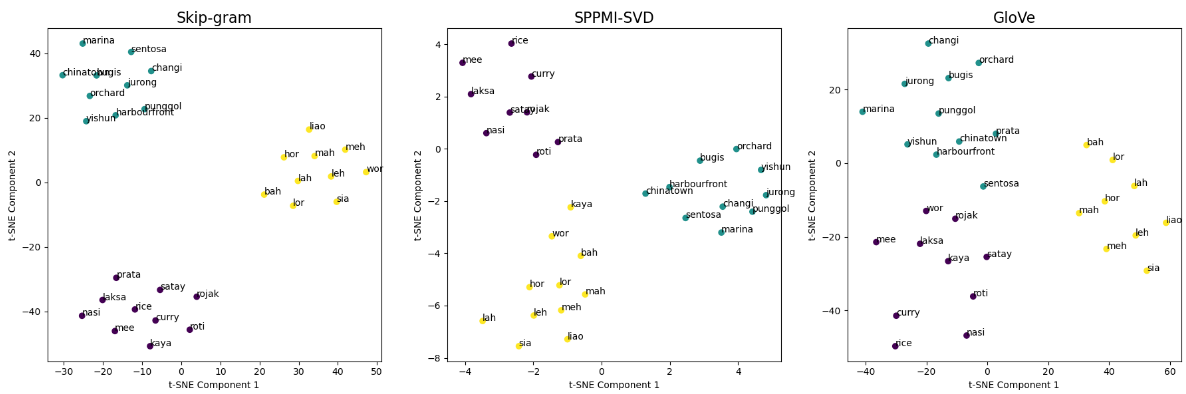
	Analogy Task	Expected	Skip-gram	SPPMI-SVD	GloVe
0	‘male‘ + ‘mom‘ - ‘dad‘	female	dictator	female	models
1	‘kopi‘ + ‘tea‘ - ‘coffee‘	teh	halia	oolong	fee
2	‘sgd‘ + ‘malaysia‘ - ‘singapore‘	ringgit	13k	ringgit	1520
3	‘teacher‘ + ‘students‘ - ‘student‘	teachers	tutor	math	senior
4	‘high‘ + ‘lower‘ - ‘low‘	higher	upper	higher	higher

3.3 Visualization of Embedding Space

In this section, we compare t-SNE visualization of the embedding space for the following Singaporean-themed word clusters between different models:

- Common Singlish particles: `lah`, `lor`, `leh`, `meh`, `liao`, `sia`, `hor`, `mah`, `bah`, `wor`
- Common Singaporean foods: `nasi`, `roti`, `prata`, `laksa`, `durian`, `satay`, `rojak`, `mee`, `kaya`, `curry`
- Common Singaporean places: `orchard`, `marina`, `sentosa`, `bugis`, `chinatown`, `yishun`, `changi`, `jurong`, `harbourfront`, `punggol`

From the visualization, all models can separate the different clusters reasonably well, especially Skip-gram where the clusters are very localized and exhibit clear boundaries from one another.



3.4 Benchmarking

This section provides a quantitative intrinsic evaluation of all models on WordSim-353, a widely used benchmark for assessing word embeddings (Finkelstein et al. 2001). We can compare the Spearman correlation between the cosine similarity of the model embeddings and the human-annotated similarity scores between our 3 models, as well as pretrained word embeddings downloaded from `gensim` library.

From the benchmarking results, it is not surprising that our models do not perform as well as the pretrained embeddings (especially those with embedding size 300), given the limited training data (millions of tokens vs. billions for pretrained models) and the nature of the CoSEM corpus being informal text messages and Singaporean English-specific. Many of the words in the test set are not in our vocabulary where our models only cover 270/353 pairs.

Among our models, SPPMI-SVD performed the best with a Spearman correlation of 0.3874, and Skip-gram followed closely behind. Surprisingly, GloVe showed much lower performance at only 0.1952.

	Model	Spearman Correlation	Pair Coverage
0	glove-twitter-50	0.4585	352/353
1	glove-wiki-gigaword-50	0.5033	353/353
2	glove-wiki-gigaword-300	0.6085	353/353
3	word2vec-google-news-300	0.6941	350/353
4	Skip-gram-50 (Ours)	0.3683	270/353
5	SPPMI-SVD-50 (Ours)	0.3874	270/353
6	GloVe-50 (Ours)	0.1952	270/353

References

Finkelstein, Lev, Evgeniy Gabrilovich, Yossi Matias, Ehud Rivlin, Zach Solan, Gadi Wolfman, and Eytan Ruppin. 2001. "Placing Search in Context: The Concept Revisited." In *Proceedings of the 10th International Conference on World Wide Web*, 406–14.

Gonzales, Wilkinson Daniel Wong, Mie Hiramoto, Jakob RE Leimgruber, and Jun Jie Lim. 2023. "The Corpus of Singapore English Messages (Cosem)." *World Englishes* 42 (2): 371–88.

klingonpigeon. 2024. "Singlish Dictionary." https://singlishdict.app/.

Levy, Omer, and Yoav Goldberg. 2014. "Neural Word Embedding as Implicit Matrix Factorization." *Advances in Neural Information Processing Systems* 27.

Mikolov, Tomas, Kai Chen, Greg Corrado, and Jeffrey Dean. 2013. "Efficient Estimation of Word Representations in Vector Space." *arXiv Preprint arXiv:1301.3781*.

Mikolov, Tomas, Ilya Sutskever, Kai Chen, Greg S Corrado, and Jeff Dean. 2013. "Distributed Representations of Words and Phrases and Their Compositionality." *Advances in Neural Information Processing Systems* 26.

Pennington, Jeffrey, Richard Socher, and Christopher D Manning. 2014. "Glove: Global Vectors for Word Representation." In *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, 1532–43.

Radim, Rehurek, and Sojka Petr. 2011. "Gensim-Python Framework for Vector Space Modelling." *NLP Centre, Faculty of Informatics, Masaryk University, Brno, Czech Republic* 3 (2).

Appendix

A.1 Conda Environment Setup

To ensure reproducibility, all code is run in a dedicated Conda environment. You can recreate this environment using the `environment.yml` file below.

```yaml
name: dsa4213-assignment-1
channels:
  - conda-forge
dependencies:
  - appnope=0.1.4=pyhd8ed1ab_1
  - asttokens=3.0.0=pyhd8ed1ab_1
  - attrs=25.3.0=pyh71513ae_0
  - brotli=1.1.0=h5505292_3
  - brotli-bin=1.1.0=h5505292_3
  - brotli-python=1.1.0=py312hd8f9ff3_3
  - bzip2=1.0.8=h99b78c6_7
  - ca-certificates=2025.8.3=hbd8a1cb_0
  - certifi=2025.8.3=pyhd8ed1ab_0
  - cffi=1.17.1=py312h0fad829_0
  - charset-normalizer=3.4.3=pyhd8ed1ab_0
  - click=8.2.1=pyh707e725_0
  - colorama=0.4.6=pyhd8ed1ab_1
  - comm=0.2.3=pyhe01879c_0
  - contourpy=1.3.3=py312ha0dd364_1
  - cycler=0.12.1=pyhd8ed1ab_1
  - debugpy=1.8.16=py312he360a15_0
  - decorator=5.2.1=pyhd8ed1ab_0
  - exceptiongroup=1.3.0=pyhd8ed1ab_0
  - executing=2.2.0=pyhd8ed1ab_0
  - fonttools=4.59.1=py312h6daa0e5_0
  - freetype=2.13.3=hce30654_1
  - gensim=4.3.2=py312h88edd18_1
  - h2=4.2.0=pyhd8ed1ab_0
  - hpack=4.1.0=pyhd8ed1ab_0
  - hyperframe=6.1.0=pyhd8ed1ab_0
  - icu=75.1=hfee45f7_0
  - idna=3.10=pyhd8ed1ab_1
  - importlib-metadata=8.7.0=pyhe01879c_1
  - ipykernel=6.30.1=pyh92f572d_0
  - ipython=9.4.0=pyhfa0c392_0
  - ipython_pygments_lexers=1.1.1=pyhd8ed1ab_0
  - jedi=0.19.2=pyhd8ed1ab_1
  - joblib=1.5.1=pyhd8ed1ab_0
  - jsonschema=4.25.1=pyhe01879c_0
  - jsonschema-specifications=2025.4.1=pyh29332c3_0
  - jupyter_client=8.6.3=pyhd8ed1ab_1
  - jupyter_core=5.8.1=pyh31011fe_0
```

```
- kiwisolver=1.4.9=py312hdc12c9d_0
- krb5=1.21.3=h237132a_0
- lcms2=2.17=h7eeda09_0
- lerc=4.0.0=hd64df32_1
- libblas=3.9.0=34_h10e41b3_openblas
- libbrotlicommon=1.1.0=h5505292_3
- libbrotlidec=1.1.0=h5505292_3
- libbrotlienc=1.1.0=h5505292_3
- libcblas=3.9.0=34_hb3479ef_openblas
- libcxx=20.1.8=hf598326_1
- libdeflate=1.24=h5773f1b_0
- libedit=3.1.20250104=pl5321hafb1f1b_0
- libexpat=2.7.1=hec049ff_0
- libffi=3.4.6=h1da3d7d_1
- libfreetype=2.13.3=hce30654_1
- libfreetype6=2.13.3=h1d14073_1
- libgfortran=15.1.0=hfdf1602_0
- libgfortran5=15.1.0=hb74de2c_0
- libjpeg-turbo=3.1.0=h5505292_0
- liblapack=3.9.0=34_hc9a63f6_openblas
- liblzma=5.8.1=h39f12f2_2
- libopenblas=0.3.30=openmp_h60d53f8_2
- libpng=1.6.50=h280e0eb_1
- libsodium=1.0.20=h99b78c6_0
- libsqlite=3.50.4=h4237e3c_0
- libtiff=4.7.0=h025e3ab_6
- libwebp-base=1.6.0=h07db88b_0
- libxcb=1.17.0=hdb1d25a_0
- libzlib=1.3.1=h8359307_2
- llvm-openmp=20.1.8=hbb9b287_1
- matplotlib=3.10.5=py312h1f38498_0
- matplotlib-base=3.10.5=py312h05635fa_0
- matplotlib-inline=0.1.7=pyhd8ed1ab_1
- munkres=1.1.4=pyhd8ed1ab_1
- nbclient=0.10.2=pyhd8ed1ab_0
- nbformat=5.10.4=pyhd8ed1ab_1
- ncurses=6.5=h5e97a16_3
- nest-asyncio=1.6.0=pyhd8ed1ab_1
- nltk=3.9.1=pyhd8ed1ab_1
- numpy=1.26.4=py312h8442bc7_0
- openjpeg=2.5.3=h889cd5d_1
- openssl=3.5.2=he92f556_0
```

```
- packaging=25.0=pyh29332c3_1
- pandas=2.3.2=py312h98f7732_0
- parso=0.8.4=pyhd8ed1ab_1
- patsy=1.0.1=pyhd8ed1ab_1
- pexpect=4.9.0=pyhd8ed1ab_1
- pickleshare=0.7.5=pyhd8ed1ab_1004
- pillow=11.3.0=py312h50aef2c_0
- pip=25.2=pyh8b19718_0
- platformdirs=4.3.8=pyhe01879c_0
- prompt-toolkit=3.0.51=pyha770c72_0
- psutil=7.0.0=py312h163523d_1
- pthread-stubs=0.4=hd74edd7_1002
- ptyprocess=0.7.0=pyhd8ed1ab_1
- pure_eval=0.2.3=pyhd8ed1ab_1
- pycparser=2.22=pyh29332c3_1
- pygments=2.19.2=pyhd8ed1ab_0
- pyparsing=3.2.3=pyhe01879c_2
- pysocks=1.7.1=pyha55dd90_7
- python=3.12.11=hc22306f_0_cpython
- python-dateutil=2.9.0.post0=pyhe01879c_2
- python-fastjsonschema=2.21.2=pyhe01879c_0
- python-tzdata=2025.2=pyhd8ed1ab_0
- python_abi=3.12=8_cp312
- pytz=2025.2=pyhd8ed1ab_0
- pyyaml=6.0.2=py312h998013c_2
- pyzmq=27.0.2=py312h211b278_0
- qhull=2020.2=h420ef59_5
- readline=8.2=h1d1bf99_2
- referencing=0.36.2=pyh29332c3_0
- regex=2025.7.34=py312h163523d_0
- requests=2.32.5=pyhd8ed1ab_0
- rpds-py=0.27.0=py312h6f58b40_0
- scikit-learn=1.7.1=py312h54d6233_0
- scipy=1.12.0=py312h9d7df2b_2
- seaborn=0.13.2=hd8ed1ab_3
- seaborn-base=0.13.2=pyhd8ed1ab_3
- setuptools=80.9.0=pyhff2d567_0
- six=1.17.0=pyhe01879c_1
- smart_open=7.3.0.post1=pyhe01879c_0
- stack_data=0.6.3=pyhd8ed1ab_1
- statsmodels=0.14.5=py312hcde60ef_0
- threadpoolctl=3.6.0=pyhecae5ae_0
```

```
  - tk=8.6.13=h892fb3f_2
  - tornado=6.5.2=py312h163523d_0
  - tqdm=4.67.1=pyhd8ed1ab_1
  - traitlets=5.14.3=pyhd8ed1ab_1
  - typing_extensions=4.14.1=pyhe01879c_0
  - tzdata=2025b=h78e105d_0
  - unicodedata2=16.0.0=py312hea69d52_0
  - urllib3=2.5.0=pyhd8ed1ab_0
  - wcwidth=0.2.13=pyhd8ed1ab_1
  - wheel=0.45.1=pyhd8ed1ab_1
  - wordcloud=1.9.4=py312hea69d52_1
  - wrapt=1.17.3=py312h163523d_0
  - xorg-libxau=1.0.12=h5505292_0
  - xorg-libxdmcp=1.1.5=hd74edd7_0
  - yaml=0.2.5=h925e9cb_3
  - zeromq=4.3.5=hc1bb282_7
  - zipp=3.23.0=pyhd8ed1ab_0
  - zstandard=0.23.0=py312hea69d52_2
  - zstd=1.5.7=h6491c7d_2
```

To create and activate the environment, run the following commands in your terminal:

```
conda env create -f environment.yml -n dsa4213-assignment-1
conda activate dsa4213-assignment-1
```

A.2 Python Code

```
import os
import random
import re
import subprocess
import zipfile
from collections import Counter

import gensim.downloader
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import requests
import seaborn as sns
```

```python
from gensim.models import KeyedVectors, Word2Vec
from gensim.scripts.glove2word2vec import glove2word2vec
from nltk.util import ngrams
from scipy.sparse.linalg import svds
from scipy.stats import spearmanr
from sklearn.manifold import TSNE
from sklearn.cluster import KMeans
from tqdm import tqdm
from wordcloud import WordCloud

if not os.path.exists("data"):
    os.makedirs("data")
if not os.path.exists("weights"):
    os.makedirs("weights")


CORPUS_URL = "https://github.com/wdwgonzales/CoSEM/raw/refs/heads/main/corpus_COSEM_v5.zip"
CORPUS_PATH = "data/corpus_COSEM_v5.zip"
EXTRACTED_PATH = "data/CoSEM_v5"
if not os.path.exists(EXTRACTED_PATH):
    if not os.path.exists(CORPUS_PATH):
        print("Downloading CoSEM corpus...")
        r = requests.get(CORPUS_URL)
        with open(CORPUS_PATH, "wb") as f:
            f.write(r.content)
        print("Download complete.")
    print("Extracting corpus...")
    with zipfile.ZipFile(CORPUS_PATH, "r") as zip_ref:
        zip_ref.extractall("data")
    os.remove(CORPUS_PATH)
    print("Extraction complete.")
else:
    print("Corpus already downloaded and extracted.")


def clean_text(text):
    """Applies a series of cleaning steps to a line of text."""
    # Convert to lowercase
    text = text.lower()
    # Remove COSEM ID, URLs, and anonymized tags
    text = re.sub(r"<<cosem\S*", "", text)
    text = re.sub(r"http\S*", "", text)
```

```
    text = re.sub(r"<.*omitted>", "", text) # i.e. <media omitted>, <link omitted>
    text = re.sub(r"{{.*}}", "", text) # i.e. {{email}}, {{twitter}}
    text = re.sub(r"\S*(?:/\S*){2,}", "", text) # i.e. D/F/CH/21, C/M/KOR/22
    # Keep only letters and numbers (remove all punctuation symbols)
    text = re.sub(r"[^a-z0-9\s]", "", text)
    # Normalize whitespace (replace multiple spaces with a single one)
    text = re.sub(r"\s+", " ", text).strip()
    return text

TEXT_FILE_PATH = "data/processed_corpus.txt"
if not os.path.exists(TEXT_FILE_PATH):
    files_to_process = [
        f for f in os.listdir(EXTRACTED_PATH) if f.startswith("COSEM_v5_chunk_")
    ]
    with open(TEXT_FILE_PATH, "w") as outfile:
        for filename in tqdm(files_to_process, desc="Processing Files"):
            filepath = os.path.join(EXTRACTED_PATH, filename)
            with open(filepath, "r") as f:
                for line in f:
                    message = clean_text(line)
                    if message:
                        outfile.write(message + "\n")
    print(f"Corpus processed and saved to {TEXT_FILE_PATH}")
else:
    print("Corpus already processed.")


# Load processed sentences
all_words = []
with open(TEXT_FILE_PATH, "r") as f:
    sentences = [line.strip().split() for line in f.readlines()]
    for sentence in sentences:
        all_words.extend(sentence)
print(f"Total sentences: {len(sentences)}")
print(f"Total words: {len(all_words)}")
print(f"Unique words: {len(set(all_words))}")
print("Example sentences:")
for s in random.sample(sentences, 3):
    print(f"- {" ".join(s)}")


# Sentence Length Distribution
```

```python
sentence_lengths = [len(sentence) for sentence in sentences]
plt.figure(figsize=(12, 6))
sns.histplot(sentence_lengths, bins=200, kde=True)
plt.title("Distribution of Sentence Lengths in CoSEM Corpus", fontsize=16)
plt.xlim(0, 20)
plt.xlabel("Number of Words per Sentence")
plt.ylabel("Frequency")
plt.savefig("sentence_length_distribution.png")
plt.show()


# Most Common Unigrams
unigram_counts = Counter(all_words)
most_common_unigrams = unigram_counts.most_common(10)
df_most_common = pd.DataFrame(
    most_common_unigrams, columns=["Unigram", "Frequency"]
)
plt.figure(figsize=(12, 6))
sns.barplot(
    x="Frequency", y="Unigram", data=df_most_common,
    palette="viridis", hue="Frequency"
)
plt.title("Top 10 Most Common Unigrams in CoSEM Corpus", fontsize=16)
plt.xlabel("Frequency")
plt.ylabel("Unigram")
plt.savefig("most_common_unigrams.png")
plt.show()


# Most Common Bigrams
bigrams = ngrams(all_words, 2)
bigram_counts = Counter(bigrams)
most_common_bigrams = bigram_counts.most_common(10)
df_most_common = pd.DataFrame(
    most_common_bigrams,
    columns=["Bigram", "Frequency"]
)
df_most_common["Bigram"] = df_most_common["Bigram"].apply(lambda x: " ".join(x))
plt.figure(figsize=(12, 6))
sns.barplot(
    x="Frequency", y="Bigram", data=df_most_common,
    palette="viridis", hue="Frequency"
```

```python
)
plt.title("Top 10 Most Common Bigrams in CoSEM Corpus", fontsize=16)
plt.xlabel("Frequency")
plt.ylabel("Bigram")
plt.savefig("most_common_bigrams.png")
plt.show()


# Word Cloud
wordcloud = WordCloud(
    width=1200,
    height=600,
    background_color="white",
).generate(" ".join(all_words))
plt.figure(figsize=(12, 6))
plt.imshow(wordcloud, interpolation="bilinear")
plt.axis("off")
plt.title("Word Cloud of CoSEM Corpus", fontsize=16)
plt.savefig("word_cloud.png")
plt.show()


# Shared Hyperparameters
VECTOR_SIZE = 50     # Dimensionality of word vectors
VOCAB_MIN_COUNT = 10 # Minimum word frequency to be included in the vocabulary
WINDOW_SIZE = 5      # Context window size
MAX_ITER = 15        # Maximum training iterations
K_NEGATIVE = 5       # Number of negative samples for Negative Sampling
NUM_THREADS = 4      # Number of training threads


# Adapted from gensim https://radimrehurek.com/gensim/models/word2vec.html
SKIPGRAM_PATH = "weights/skipgram.model"
if not os.path.exists(SKIPGRAM_PATH):
    print(f"Skip-gram vectors not found at {SKIPGRAM_PATH}. Training...")
    skipgram_model = Word2Vec(
        sentences, vector_size=VECTOR_SIZE, window=WINDOW_SIZE,
        min_count=VOCAB_MIN_COUNT, sg=1, hs=0, negative=K_NEGATIVE,
        ns_exponent=0.75, epochs=MAX_ITER, workers=NUM_THREADS
    )
    skipgram_model.save(SKIPGRAM_PATH)
    print(f"Skip-gram training complete. Vectors saved to {SKIPGRAM_PATH}.")
```

```
else:
    print("Skip-gram model already exists. Loading from disk.")
    skipgram_model = Word2Vec.load(SKIPGRAM_PATH)
print(f"Skip-gram model vocabulary size: {len(skipgram_model.wv.key_to_index)}")


# Adapted from DSA4213 Lecture Slides
SPPMI_SVD_PATH = "weights/sppmi_svd.model"
CO_OCCURRENCE_MATRIX = "weights/co_occurrence_matrix.npy"
SPPMI_MATRIX = "weights/sppmi_matrix.npy"
if not os.path.exists(SPPMI_SVD_PATH):
    print(f"SPPMI-SVD vectors not found at {SPPMI_SVD_PATH}. Training...")
    print("\n--- 1. Building Vocabulary ---")
    word_counts = Counter(all_words)
    vocab = {
        word: count for word, count in word_counts.items()
        if count >= VOCAB_MIN_COUNT
    }
    vocab = {word: idx for idx, word in enumerate(vocab.keys())}
    vocab_size = len(vocab)
    print(f"SPPMI-SVD vocabulary size: {vocab_size}")
    print("\n--- 2. Building Co-occurrence Matrix ---")
    if not os.path.exists(CO_OCCURRENCE_MATRIX):
        co_matrix = np.zeros((vocab_size, vocab_size), dtype=np.float32)
        for sentence in tqdm(sentences, desc="Processing sentences"):
            sentence_length = len(sentence)
            for idx, word in enumerate(sentence):
                if word in vocab:
                    start = max(0, idx - WINDOW_SIZE)
                    end = min(sentence_length, idx + WINDOW_SIZE + 1)
                    for context_idx in range(start, end):
                        if idx != context_idx and sentence[context_idx] in vocab:
                            co_matrix[vocab[word], vocab[sentence[context_idx]]] += 1
        np.save(CO_OCCURRENCE_MATRIX, co_matrix)
    else:
        co_matrix = np.load(CO_OCCURRENCE_MATRIX)
    print("Co-occurrence matrix built.")
    print("\n--- 3. Computing SPPMI Matrix ---")
    if not os.path.exists(SPPMI_MATRIX):
        co_occurrence_sum = np.sum(co_matrix)
        p_word = np.sum(co_matrix, axis=1) / co_occurrence_sum
        sppmi_matrix = np.zeros_like(co_matrix)
```

```
        for i in tqdm(range(vocab_size), desc="Computing SPPMI"):
            for j in range(vocab_size):
                if co_matrix[i, j] > 0:
                    pmi = np.log(
                        (co_matrix[i, j] / co_occurrence_sum) /
                        (p_word[i] * p_word[j])
                    )
                    # Shifted Positive PMI
                    sppmi_matrix[i, j] = max(pmi - np.log(K_NEGATIVE), 0)
        np.save(SPPMI_MATRIX, sppmi_matrix)
    else:
        sppmi_matrix = np.load(SPPMI_MATRIX)
    print("SPPMI matrix computed.")
    print("\n--- 4. Performing SVD ---")
    # Faster than np.linalg.svd on sparse matrices
    U, Sigma, Vt = svds(sppmi_matrix, k=VECTOR_SIZE)
    print("SVD complete.")
    print("\n--- 5. Saving SPPMI Vectors in Word2Vec Format ---")
    Sigma_k = np.diag(Sigma)
    Sigma_k_sqrt = np.sqrt(Sigma_k)
    sppmi_embeddings = U @ Sigma_k_sqrt
    with open(SPPMI_SVD_PATH, "w") as f:
        f.write(f"{vocab_size} {VECTOR_SIZE}\n")
        for word, idx in vocab.items():
            vector_str = " ".join(map(str, sppmi_embeddings[idx]))
            f.write(f"{word} {vector_str}\n")
else:
    print("SPPMI-SVD model already exists. Loading from disk.")
sppmi_svd_model = KeyedVectors.load_word2vec_format(SPPMI_SVD_PATH)


# Follow installation instructions from https://github.com/stanfordnlp/GloVe
!git clone https://github.com/stanfordnlp/GloVe.git
!cd GloVe && make

# Adapted from https://github.com/stanfordnlp/GloVe/blob/master/demo.sh
CORPUS = "data/processed_corpus.txt"
VOCAB_FILE = "weights/glove_vocab.txt"
COOCCURRENCE_FILE = "weights/glove_cooccurrence.bin"
COOCCURRENCE_SHUF_FILE = "weights/glove_cooccurrence.shuf.bin"
BUILDDIR = "GloVe/build"
SAVE_FILE = "weights/glove_vectors"
```

```python
VERBOSE = "2"
MEMORY = "4.0"
BINARY = "2"
X_MAX = "10"
FINAL_SAVE_FILE = f"{SAVE_FILE}.txt"

if not os.path.exists(FINAL_SAVE_FILE):
    print(f"GloVe vectors not found at {FINAL_SAVE_FILE}. Training...")

    print("\n--- 1. Building Vocabulary ---")
    vocab_command = [
        f"{BUILDDIR}/vocab_count",
        "-min-count", str(VOCAB_MIN_COUNT),
        "-verbose", VERBOSE
    ]
    with open(CORPUS, "r") as f_corpus, open(VOCAB_FILE, "w") as f_vocab:
        subprocess.run(vocab_command, stdin=f_corpus, stdout=f_vocab)
    print(f"Vocabulary file created at {VOCAB_FILE}")
    print("\n--- 2. Building Co-occurrence Matrix ---")
    cooccur_command = [
        f"{BUILDDIR}/cooccur", "-memory", MEMORY,
        "-vocab-file", VOCAB_FILE, "-verbose", VERBOSE,
        "-window-size", str(WINDOW_SIZE)
    ]
    with open(CORPUS, "r") as f_corpus, open(COOCCURRENCE_FILE, "wb") as f_cooccur:
        process = subprocess.run(cooccur_command, stdin=f_corpus, stdout=f_cooccur)
    print(f"Co-occurrence file created at {COOCCURRENCE_FILE}")
    print("\n--- 3. Shuffling Co-occurrence Data ---")
    shuffle_command = [
        f"{BUILDDIR}/shuffle", "-memory", MEMORY, "-verbose", VERBOSE
    ]
    with open(COOCCURRENCE_FILE, "rb") as f_cooccur, open(COOCCURRENCE_SHUF_FILE, "wb") as f_
        process = subprocess.run(shuffle_command, stdin=f_cooccur, stdout=f_shuf)
    print(f"Shuffled co-occurrence file created at {COOCCURRENCE_SHUF_FILE}")
    print("\n--- 4. Training GloVe Model ---")
    glove_command = [
        f"{BUILDDIR}/glove", "-save-file", SAVE_FILE,
        "-threads", str(NUM_THREADS), "-input-file", COOCCURRENCE_SHUF_FILE,
        "-x-max", X_MAX, "-iter", str(MAX_ITER),
        "-vector-size", str(VECTOR_SIZE), "-binary", BINARY,
        "-vocab-file", VOCAB_FILE, "-verbose", VERBOSE
    ]
```

```
    process = subprocess.run(glove_command)
    print(f"GloVe training complete. Vectors saved to {SAVE_FILE}.txt")
else:
    print(f"GloVe vectors already exist at {FINAL_SAVE_FILE}. Skipping training.")

# Load the GloVe vectors into gensim
GLOVE_PATH = f"weights/glove.model"
if not os.path.exists(GLOVE_PATH):
    print("Converting GloVe format to Word2Vec format...")
    glove2word2vec(FINAL_SAVE_FILE, GLOVE_PATH)
else:
    print("GloVe Word2Vec format already exists. Loading from disk.")
glove_model = KeyedVectors.load_word2vec_format(GLOVE_PATH)


models = [
    (skipgram_model.wv, "Skip-gram"),
    (sppmi_svd_model, "SPPMI-SVD"),
    (glove_model, "GloVe"),
]


# Nearest Neighbors
words = ["kiasu", "chope", "paiseh", "sian" ,"dabao"]
for word in words:
row_data = {}
    for model, model_name in models:
        entries = []
        if word in model:
            similar_words = model.most_similar(word, topn=5)
            for rank, (similar_word, _) in enumerate(similar_words, 1):
                entries.append(similar_word)
        else:
            entries = ["Not in vocabulary"] * 5
        row_data[model_name] = entries
    df = pd.DataFrame.from_dict(
        row_data, orient="index",
        columns=[f"Rank {i}" for i in range(1, 6)]
    )
    display(df)

# Word Analogy Task
```

```python
analogies = [
    ("dad", "mom", "male", "female"), # gender
    ("coffee", "tea", "kopi", "teh"), # food
    ("singapore", "malaysia", "sgd", "ringgit"), # currency
    ("student", "students", "teacher", "teachers"), # pluralization
    ("low", "lower", "high", "higher"), # comparison
]
def get_analogy_prediction(model, a, b, c):
    """Performs the analogy task and returns the top predicted word."""
    if all(word in model for word in [a, b, c]):
        result = model.most_similar(positive=[c, b], negative=[a], topn=1)
        return result[0][0]
    return "NA"
results = []
for a, b, c, expected in analogies:
    sg_pred = get_analogy_prediction(skipgram_model.wv, a, b, c)
    sppmi_pred = get_analogy_prediction(sppmi_svd_model, a, b, c)
    glove_pred = get_analogy_prediction(glove_model, a, b, c)
    results.append({
        "Analogy Task": f"`{c}` + `{b}` - `{a}`",
        "Expected": expected,
        "Skip-gram": sg_pred,
        "SPPMI-SVD": sppmi_pred,
        "GloVe": glove_pred
    })
df = pd.DataFrame(results)
display(df)


# Visualization of Embedding Space
words = [
    # Common Singlish particles
    "lah", "lor", "leh", "meh", "liao", "sia", "hor", "mah", "bah", "wor",
    # Common food in Singapore
    "nasi", "roti", "prata", "laksa", "rice",
    "satay", "rojak", "mee", "kaya", "curry",
    # Common places in Singapore
    "orchard", "marina", "sentosa", "bugis", "chinatown",
    "yishun", "changi", "jurong", "harbourfront", "punggol"
]
fig, axes = plt.subplots(1, len(models), figsize=(6 * len(models), 6))
for ax, (model, model_name) in zip(axes, models):
```

```
    embeddings = model[words]
    tsne = TSNE(n_components=2, random_state=42, perplexity=10)
    reduced_embeddings = tsne.fit_transform(embeddings)
    kmeans = KMeans(n_clusters=3, random_state=42, n_init='auto')
    cluster_labels = kmeans.fit_predict(reduced_embeddings)
    scatter = ax.scatter(
        reduced_embeddings[:, 0],
        reduced_embeddings[:, 1],
        marker='o',
        c=cluster_labels,
        cmap='viridis'
    )
    for i, word in enumerate(words):
        ax.annotate(
            word,
            xy=(reduced_embeddings[i, 0], reduced_embeddings[i, 1]),
            fontsize=10
        )
    ax.set_title(f"{model_name}", fontsize=16)
    ax.set_xlabel("t-SNE Component 1")
    ax.set_ylabel("t-SNE Component 2")
plt.tight_layout()
plt.savefig("embedding_visualization.png")
plt.show()


# Wordsim-353 Benchmark
WORDSIM_353_URL = 'https://gabrilovich.com/resources/data/wordsim353/wordsim353.zip'
WORDSIM_353_PATH = 'data/wordsim353.zip'
WORDSIM_353_FILE = 'data/wordsim353.csv'
if not os.path.exists(WORDSIM_353_FILE):
    print("Downloading WordSim-353 dataset...")
    r = requests.get(WORDSIM_353_URL)
    with open(WORDSIM_353_PATH, 'wb') as f:
        f.write(r.content)
    with zipfile.ZipFile(WORDSIM_353_PATH, 'r') as zip_ref:
        zip_ref.extractall('data')
    os.rename('data/combined.csv', WORDSIM_353_FILE)
    os.remove(WORDSIM_353_PATH)
    print(f"Download complete.")
else:
    print(f"WordSim-353 dataset already exists at {WORDSIM_353_FILE}")
```

```python
def wordsim353_evaluate(name, model):
    """Evaluates a Gensim KeyedVectors model on the WordSim-353 dataset."""
    df = pd.read_csv(WORDSIM_353_FILE)
    human_scores = []
    model_scores = []
    for _, row in df.iterrows():
        word1 = str(row['Word 1']).lower()
        word2 = str(row['Word 2']).lower()
        human_score = row['Human (mean)']
        if word1 in model.key_to_index and word2 in model.key_to_index:
            model_score = model.similarity(word1, word2)
            human_scores.append(human_score)
            model_scores.append(model_score)
    correlation, _ = spearmanr(human_scores, model_scores)
    return {
        "Model": name,
        "Spearman Correlation ( )": f"{correlation:.4f}",
        "Pair Coverage": f"{len(human_scores)}/{len(df)}"
    }

results = []
# Evaluate pre-trained models
benchmarks = [
    'glove-twitter-50',
    'glove-wiki-gigaword-50',
    'glove-wiki-gigaword-300',
    'word2vec-google-news-300'
]
for model_name in benchmarks:
    model = gensim.downloader.load(model_name)
    results.append(wordsim353_evaluate(model_name, model))
# Evaluate our own models
results.append(wordsim353_evaluate("Skip-gram-50 (Ours)", skipgram_model.wv))
results.append(wordsim353_evaluate("SPPMI-SVD-50 (Ours)", sppmi_svd_model))
results.append(wordsim353_evaluate("GloVe-50 (Ours)", glove_model))
df = pd.DataFrame(results)
display(df)
```

A.3 AI Tool Declaration

I used Gemini 2.5 Pro and Github Copilot to generate ideas, format paragraphs, improve expression, produce drafts, refine, and finalize my assignment. I am responsible for the content and quality of the submitted work.